A Review on Detection of Coronavirus (COVID-19) Disease from Chest X-Ray Images using Deep Learning Methods

Chander Deep Singh [1], Dinesh Kumar Garg [2]

[1] Master of Technology Student, [2] Associate Professor & Head
[1, 2] Department of Computer Science & Engineering, Sri Sai College of Engineering & Technology
Badhani, Pathankot, Punjab, India

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Abstract
The COVID-19 disease, which was brought on by the SARS-CoV-2 virus, spread quickly, highlighting the critical need for sensitive, quick, and accurate diagnostic methods. Finding asymptomatic instances that result in the propagation of the virus to close contacts is actually one of the primary hurdles for flattening COVID-19 distribution charts. The COVID-19 infections must still be detected even after immunisation because to the SARS-CoV-2 virus's rather quick mutation. However, due to a number of drawbacks, including low specificity and sensitivity, a quick, inexpensive, and simple approach is required for the diagnosis of COVID-19. Conventional techniques, which are commercially available, have focused on clinical manifestation, along with molecular and serological detection tools that can identify the SARS-CoV-2 virus. Today, there is a great deal of interest among scientists in developing a quick, portable test for COVID-19. Numerous cutting-edge techniques and strategies are regarded as workable sophisticated systems that can satisfy the demands. This article discusses recent methods and sensing innovations that support COVID-19 diagnosis for quick and accurate SARSCoV-2 viral identification.

Keywords: Corona Virus, COVID-19, Chest X-ray, Disease Detection, Deep Learning, CNN, Convolutional Neural Network, RT-PCR, CT Scan

1. Introduction

Fighting virally transmitted infectious illnesses is very challenging and is considered as continuing public health care effort [1]. Coronaviruses, which are members of Coronaviridae family, can harm nervous system and cause respiratory issues. Six human coronaviruses (HCoV) have been found, including Middle East respiratory illness coronavirus, HCoV-229E, HCoV-HKU1, HCoV-OC43, HCoV NL63, and SARS-CoV. SARS-CoV and MERS-CoV are two of them that have previously caused pandemics [2]. Coronavirus disease 2019, also known as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), is most recent and severe coronavirus. COVID-19, most severe epidemic in last 100 years, is believed to have started in Wuhan, China, in late 2019 [3].

In March 2019, World Health Organization declared a pandemic. COVID-19 virus has hazy symptoms that are similar to the flu. Coronavirus sickness first manifests as respiratory ailments like cough, fever, and breathing problems. Due to vast variation in severity of disease, a population is defined as those who do not undergo examination at time of acute infection but instead only show minimal symptoms or none at all. More than 94 million COVID-19 cases and more than 2 million verified deaths have been reported worldwide as of March 2021. Millions of people's living and working conditions have been seriously harmed by various forms of social isolation and city lockdowns [4].

Social isolation and ongoing, inclusive, and widespread testing continue to be the most effective ways to stop the spread of the COVID-19 virus, despite the recent development of COVID-19 vaccines and their administration to high-risk populations. This is especially true given that vaccination rates are very low in comparison to the rate at which the virus spreads. It is still essential to adopt a consistent diagnostic technique to break the chain of transmission because the SARS-CoV-2 virus has a high rate of transmission, is novel in many respects, and has produced numerous issues for countries all over the world to manage it. According to WHO findings, more than 30% of virus carriers don't show any symptoms, making swift and precise detection of the SARS-CoV-2 virus essential for early diagnosis of COVID-19, which is crucial for limiting virus spread and saving lives of susceptible groups [5]. Up until now, there have been numerous reports on discovery of new coronaviruses using a number of methods. For other members of Coronaviridae family, many strategies have been used in past, and other brand-new techniques have only recently been discovered for SARS-CoV-2.

First laboratory test for diagnosis of COVID-19 is RT-PCR, or reverse transcription-polymerase chain reaction. Coronaviruses only contain Ribonucleic Acid, which must be converted to Deoxyribonucleic Acid for amplification, hence RT-PCR method is utilised to detect them. While it has advantages, it also takes long time, which raises the possibility that an infected person would spread disease, and deep nasal swabs are uncomfortable. Early illness diagnosis is crucial in order to isolate positive people as soon as possible and prevent disease from spreading across population. Because lung region is area that is often impacted by virus, medical imaging modalities like X-ray and CT are typically taken into account in order to assess degree of infection. [6].

Because of their widespread availability, quick turnaround, and low cost, X-ray imaging techniques are often used for the diagnosis of COVID-19. However, because they offer thorough information on the affected area, CT imaging techniques are advised. Finding infection from medical imaging has become challenging, even for experienced radiologists, due to a lack of in-depth knowledge of disease. Deep learning algorithms in conjunction with images of medical conditions have shown to be a successful method for diagnosing COVID-19 [7]. The objective of this article is to compile the workflow of recent studies on the automated detection of COVID-19 using deep learning methods. This essay compares the exceptional features of the most recent deep learning approaches. It also provides reasonable framework for future researchers to develop DL models that have great chance of detecting illnesses early on.

The remainder of this paper is organised as follows: Section 2 discusses pre-processing methods for producing high-quality medical photographs. The pre-trained models that are frequently utilised for COVID-19 identification are covered in Section 3. The binary and multiclass classification of data records is covered in Section 4. The article is concluded in Section 5, where other researchers are given ideas for additional study to conduct.

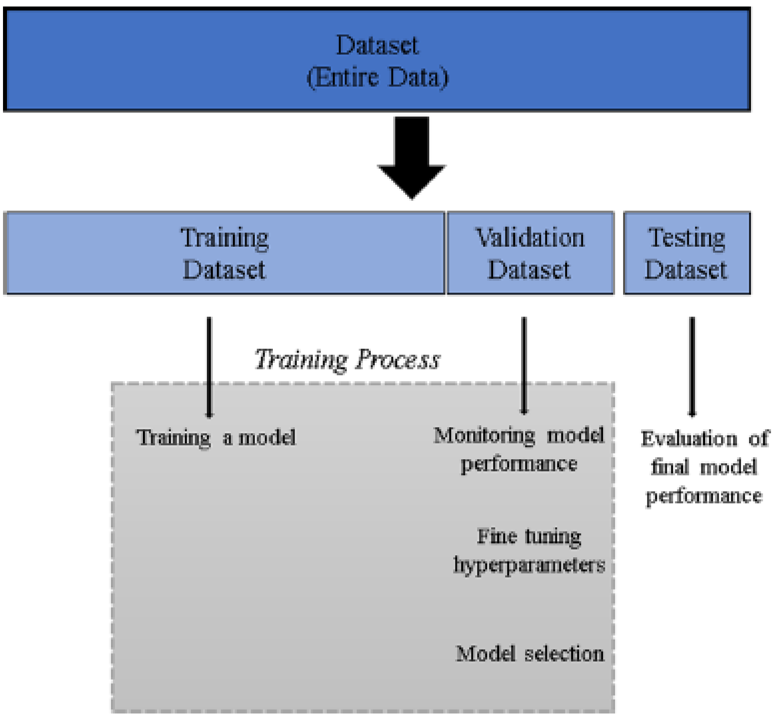
2. Preprocessing of the Data

Medical imaging is a technology that uses images of a person's internal organs to diagnose a variety of medical issues. X-ray and CT imaging are the two medical imaging modalities that are most frequently used to detect COVID-19. The limits and margins, however, are not readily evident due to the pictures' low intensity and contrast, which could lead to an incorrect disease diagnosis. Therefore, it is essential to pre-process medical images in order to extract the relevant information and eliminate the remainder in order to increase the model's accuracy [8]. Medical image processing is the process of improving the image quality of unprocessed medical data in preparation for future investigation. It includes processing a digital image with an algorithm. In medical imaging applications, visual information of input image is enhanced utilising a number of pre-processing techniques. Images that have undergone standard pre-processing techniques for COVID-19 diagnosis in X-rays and CT scans include picture scaling, image segmentation, and image enhancement.

3. Background of Deep Learning Classification

Deep learning requires a lot of data in order to train model efficiently and precisely. Dataset contains three pieces of data: test dataset, validation dataset and training dataset. Using training dataset, model is taught new tasks as part of learning process. During training phase, model hyper parameters are evaluated and adjusted using validation dataset to improve model selection. Test dataset is used to evaluate model once it has been fully trained using training and validation datasets. Usual split of dataset is shown in Fig. 1. Supplied datasets are insufficient and unbalanced for model to be adequately trained because COVID-19 is a persistent and recent epidemic [9].

Figure 1: General Classification Method



In this section, a brief overview of CNN architectures and main points on available different architectures are presented.

3.1. Convolutional Neural Networks

Artificial neural networks, more especially convolutional neural networks, are a subset of deep learning techniques that draw their inspiration from the visual perception system found in biological things [10]. The only thing that CNNs are is stacked, multilayered neural networks. Convolutional layers, pooling layers, and completely linked layers are the three main types of layers. Any CNN model starts with an input layer, where the input parameters are the width, height, and depth of the input image. Convolutional layers are defined following the input layer, with the parameters being the number of filters, filter window size, stride, padding, and activation. By computing the weighted total, convolutional layers are used to extract useful feature maps for the input location. Next, an activation function is applied to each feature map, and bias is then added to create output. Typically, activation function is rectilinear unit (ReLU) activation[11].

3.2. Transfer Learning

Number of epochs is specified to begin training after designing, fabricating, and developing a DL model. Random weights are initialised during training and modified at the end of each epoch to bring outcome closer to classification score. However, with transfer learning, model can be initialised with weight values from pretrained models rather of utilising random weight values. When training data is scarce, transfer learning performs best. When performing transfer learning, final layer of pretrained model architecture is swapped out with fully connected layer with same no. of classes as new dataset. Architecture is retrained to use model for new dataset [12].

3.3. Fine-tuning

When dataset is small, fine-tuning is also used. The final layer of architecture is replaced and redefined, much like transfer learning. One layer can be redefined and retrained according to application during fine-tuning, whereas all layers are retrained during transfer learning [13]. The inability to alter input image's size is one of these approaches' biggest drawbacks. Resizing picture is therefore required if pretrained model utilises smaller image dimension and transfer learning needs to be done on dataset with bigger image dimension. In some circumstances, downsizing a huge image to smaller image can influence model's performance. The implementation of transfer learning and fine-tuning must be done with great care.

3.4. AlexNet

Simple convolutional neural network with five layers. VGG network comes in two different forms: VGG16 and VGG19. VGG architecture was first suggested for use in image recognition software. VGG16 and VGG19 use 16 and 19 weight layers with a 3×3 convolutional filter size. In 2014, network placed first and second in ILSVR (ImageNet) contest. The supplied image's dimensions are set to 224×224. ImageNet dataset, which includes millions of images, is used to train model [14].

3.5. ResNet

It is also employed in image classification techniques, and it won 2015 ILSVRC [15]. The ResNet family uses the residual block, which is a network-in-network in their architecture. Network is defined in five phases with convolutional and identity blocks. Input image size is 224×224, which is same as VGG family. There are numerous options accessible.

3.6. InceptionNet

InceptionNet introduces new architecture with an inception block as opposed to CNN topologies, in which layers are piled [16]. Inception family members come in a variety of forms. The inception network took part in 2014 ILSVR (ImageNet) competition and is used for picture categorization and localization. Authors simultaneously apply different filter sizes to input image in inception block rather than increasing depth of model by adding more layers. Model width increases as a result. Next inception block receives a concatenated version of all inception block's outputs.

4. Literature Review

Matias Cam Arellano and Oscar E. Ramos [17]

They utilized DenseNet121 pre-trained CNN model, whose last layer has been specifically trained to detect COVID-19 from chest radiographs utilizing public databases. Because model has already been taught to identify various lung diseases, it was 94.7% accurate in identifying distinguishing traits.

Abhijit Bhattacharyya et al. [18]

Using three-step procedure, COVID-19 and pneumonia can be identified from chest X-ray pictures. Lung region is initially segmented from CXR images using Conditional Generative Adversarial Network. Features are extracted from segmented lung pictures in second stage by feature extraction network, which combines deep CNNs and conventional feature extraction algorithms. CXR images were classified using several ML classifiers in last phase using retrieved features. With classification accuracy of 96.6%, Binary Robust Invariant Scale Key-points and VGG-19 generated best results.

Khandaker Foysal Haque et al. [19]

They created CNN model that successfully detected COVID-19 from CXR pictures with an accuracy of 97.56%. When compared to models trained with three and five convolutional layers, suggested model with four convolutional layers performed better.

Md Zabirul Islam et al. [20]

To automatically detect COVID-19 from chest X-ray pictures, a combination Convolutional Neural Network Long- & Short-Term Memory was developed. The model, which utilized LSTM to categorize abnormality and CNN to extract deep features, produced an accuracy of 99.4%.

Linda Wang et al. [21]

One of first open-source designs for recognizing COVID-19 from CXR images was a DCNN called COVID-Net, which was introduced. Authors produced open-access dataset COVIDx, which is tested on COVID-Net, VGG-19, and ResNet 50, by combining five separate open-access datasets. COVID-Net did well, as evidenced by its accuracy of 93.3%.

Khalid El Asnaoui et al. [22]

They examined seven deep learning models for identifying and categorizing COVID-19 pneumonia. With data augmentation and transfer learning, Inception-ResNet V2 achieved greatest accuracy of 92.18% from pre-processed input CT and X-ray images.

M. El-Kenawy et al. [23]
It was suggested to employ two steps of Advanced Squirrel Search Optimization Algorithm to categorize various abnormalities from X-ray pictures. In first stage, trained ResNet 50 model is utilized to extract features, and in second stage, suggested ASSOA algorithm is used to choose features. The classification of infected cases uses a Multilayer Perceptron Neural Network. When utilizing Kaggle dataset, accuracy was 99.26%, and when using chest X-ray COVID-19 GitHub pictures, it was 99.7%.

Pradeep Kumar Chaudhary and Ram Bilas Pachori [24]
They introduced the Fourier-Bessel series expansion-based dyadic decomposition (FBD), which divides an X-ray image into sub-band images. The pre-trained ResNet50 model receives each sub-band image, from which deep features are retrieved. The collected features are combined and supplied to softmax classifier, which distinguished between COVID-19-caused pneumonia and other types of pneumonia with a 98.66% accuracy.

Afshar Shamsi et al. [25]
A system based on transfer learning, that is uncertainty aware and can identify COVID-19 infected cases from CT and X-ray images, has been proposed. To achieve classification task, four pre-trained models are employed for feature extraction, and these features are then fed into deep learning models. With an accuracy of 87.9%, ResNet 50 model and Support Vector Machine classifier produced best outcomes.

Zhanget et al. [26]
It was suggested to use multi-input deep convolutional attention network (MIDCAN) that could process both 2D and 3D chest X-ray and computed tomography images simultaneously. The model is updated with new convolutional block attention module (CBAM) to increase its accuracy to 98.02±1.35%.

Chaimae Ouchicha et al. [27]
They developed sophisticated method called CVDNet for detection of COVID-19 from chest X-ray images. To distinguish between local and global features, it comprises of two parallel columns with same structures but different kernel sizes. Concatenating results from two columns, the model produced accuracy of 96.69%.

Ioannis D. Apostolopoules and Tzani A. Mpesiana [28]
They examined how well the most recent CNN models for medical image classification worked. A transfer learning method is used to identify various abnormalities from medical photos with small datasets. This method produced classification accuracy of 96.78% for binary classification and 94.72% for multiclass classification.

Tulin Ozturk et al. [29]
They introduced DarkCovidNet, a deep CNN model for COVID-19 detection from raw X-ray pictures. For binary classification, accuracy was achieved at 98.08%, and for multiclass classification, accuracy was achieved at 87.02%.

Tanvir Mahmud et al. [30]
They introduced a deep learning model called CovXNet that made use of depthwise convolution and effectively extracted characteristics from chest x-ray pictures. Model is trained to detect COVID-19

from smaller database using fine-tuned pre-trained convolutional layers. A ccuracy for two-class classification is 97.4%, and accuracy for multiclass classification is 90.02%.

Ioannis D. Apostopoulos et al. [31]

They used MobileNet to identify anomalies in three different ways from chest X-ray pictures. For seven class and binary classification, the MobileNet trained from scratch outperformed the other two methods. For binary classification, this method had a 99.18% accuracy rate, and for multiclass classification, it had an 87.66% accuracy rate.

Suat Toramanet et al. [32]

To detect COVID-19 from CXR images with less layers, a convolutional CapsNet, an artificial neural network based on capsule networks, was proposed. The accuracy attained with this method is 97.24% for binary classification and 84.22% for multiclass classification.

5. Conclusion

Social seclusion and early discovery are the only preventive measures currently available for the COVID-19 pandemic, a distinct pandemic caused by a coronavirus. For the purpose of early disease detection and disease prevention, deep learning algorithms are trained to identify and classify COVID-19 patients. The COVID-19 epidemic only just started to spread in the fourth quarter of 2019, thus there aren't many data points from which to train deep learning models. To overcome this limitation, researchers constructed datasets using a variety of repositories. The study's strategies include transfer learning on well-established designs, new architectures incorporating transfer learning, and other approaches, as well as deep feature extraction using a deep learning architecture and hierarchical classification technique. Worldwide immunization programmes are in place, but among the major issues are supply chain logistics and vaccine apprehension. There are now just a few RT-PCR kits available because of the sudden rise of COVID-19 cases. The use of medical imaging in conjunction with deep learning algorithms is particularly advantageous for producing speedier and more accurate results in the midst of COVID-19's rapid spread. In some instances, transfer learning performs better and is more accurate than other currently used techniques. Deep learning models perform better when trained on larger datasets.

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