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A Review on Detection of COVID-19 Cases from Medical Images Using Machine Learning-Based Approach

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Abstract

The COVID-19 pandemic (the form of coronaviruses) developed at the end of 2019 and spread rapidly to almost every corner of the world. It has infected around 25,334,339 of the world population by the end of September 1, 2020. It has been spreading ever since, and the peak specific to every country has been rising and falling and does not seem to be over yet. Currently, the conventional RT-PCR testing is required to detect COVID-19, but the alternative method for data archiving purposes is certainly another choice for public departments to make. Researchers are trying to use medical images such as X-ray and Computed Tomography (CT) to easily diagnose the virus with the aid of Artificial Intelligence (AI)-based software. This review paper provides an investigation of a newly emerging machine-learning method used to detect COVID-19 from X-ray images instead of using other methods of tests performed by medical experts. The facilities of computer vision enable us to develop an automated model that has clinical abilities of early detection of the disease. We have explored the researchers' focus on the modalities, images of datasets for use by the machine learning methods, and output metrics used to test the research in this field. Finally, the paper concludes by referring to the key problems posed by identifying COVID-19 using machine learning and future work studies. This review's findings can be useful for public and private sectors to utilize the X-ray images and deployment of resources before the pandemic can reach its peaks, enabling the healthcare system with cushion time to bear the impact of the unfavorable circumstances of the pandemic.

Keywords

Detection, COVID-19, Coronavirus, Medical Images, Artificial Intelligence

1. Introduction

The new coronavirus becoming an ongoing public health concern worldwide since mid-December 2019 onward, and three months after its emergence in Wuhan (China), so it was declared pandemic (COVID-19) by the World Health Organization (WHO). According to WHO, coronaviruses belong to the large common cold, dangerous diseases, affecting humans with itchy and flowing, breathing difficulties. COVID-19 Pandemic Disease Virus has been likened to as SARS-CoV-2 as extreme acute coronavirus syndrome 2 (C. Huang *et al.*, 2020), (C. Huang *et al.*, 2020) (J. Cui, F. Li, and Z. L. Shi, 2019). Coronaviruses (CoV) is a comprehensive category of a medical condition caused by diseases such as the Middle East Respiratory Syndrome (MERS-CoV) and Severe Acute Respiratory Syndrome (SARS-CoV) (W. C. Culp, 2020). Coronavirus Disease (COVID-19) is a new species discovered in December 2019 that humans have not previously experienced.

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The easiest way to transfer the virus is through the air and physical contact or proximity with an infected person, such as a hand or even close to the person less than three meters (C. C. Lai, T. P. Shih, W. C. Ko, H. J. Tang, and P. R. Hsueh, 2020). The most common symptoms are fever, dry cough, and muscle fatigue. According to the latest reports, over one million people across the two hundred countries have been infected. About sixty thousand confirmed deaths are reported until the end of September 2020 (C. R. Dennison Himmelfarb and D. Baptiste, 2020). The Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) illustrated the Dashboard shown in Figure 1.

Figure 1 Total Case, Total Death from (JHU).

Public health department clinicians currently use the Reverse Transcription Polymerase Chain Reaction (RT-PCR) test to detect nucleic acid forms stemming from SARS-CoV-2. Furthermore, these tests have a lower detection rate of between 30% to 50%. Therefore, to confirm the diseases, it needs to be replicated most of the time, a manual and complex method (C. C. Lai, et al., 2020). As an alternative to the traditional RT-PCR technique, researchers have proposed using medical images of Computed Tomography (CT) and chest X-rays (CXRs) to detect COVID-19 through what is referred to as an alternative technique (W. Choi *et al.*, 2020) (M. Hammad, et al. 2018).

Machine Learning (ML) methods have been heavily used in many of the medical fields, including diseases such as cardiovascular classification (H. Greenspan, B. Van Ginneken, and R. M. Summers, 2016) (A. S. Alghamdi, et al. 2020), the classification of diabetic retinopathy, or those related to intraocular pressure level types (D. B. Mule, et al. 2019). These techniques have shown the ability to reduce medical errors, early detection, and monitoring of asymptomatic signs or symptoms of infection, illness, or disease. Such processing of images has been proving to help enhance the treatment of diseases and provide appropriate healthcare for patients.

This paper has selected COVID-19 outbreaks due to the virus' unprecedented spread rate worldwide and the rapid temporal progression of the disease across the subjects' body. Therefore, a faster screening tool is needed to detect COVID-19 massive scale will be a good option to explore. This review paper includes papers that have been published in the detection area of COVID-19 and a comprehensive review on detection COVID-19 research efforts with a particular focus on limited datasets. The query range has been made from the end of 2019, which is the year the COVID-19 appeared until the beginning of 2020; however, some research is excluded for reasons.

The paper is organized as follows Section 3 explains datasets and resources used in the detection process. Section 4 discusses machine learning techniques and the performance measure used for evaluation. Section 5 discusses in more detail the selected papers for review. And finally, the main challenges faced in the detection of COVID-19 using a deep learning approach and future research work are presented.

2. COVID-19 Datasets and Resource

These review papers present almost all the used datasets from the reviewed papers and detection them based on the types of medical images. Most of the paper's detection based on modality images. There are different medical images, such as MRI (magnetic resonance imaging), ultrasound, Computed tomography (CT), and X-RAY. However, just two types of medical images can clarify the lung opacity infected by COVID-19 [10]. On the other hand, most papers combine different dataset sources to scale large datasets during detection. As a result, many researchers used x-ray images rather than CT images. Table 1 shows public COVID-19 datasets available on the internet. It contains name datasets, sources, types of medical images (modality).

1. **X-ray images sources:** There are many X-ray images available more than other medical images. Moreover, an X-ray detects infected bodies such as bones, infection of lungs, and pneumonia. Therefore, using X-RAY is a common scan. However, almost all hospitals have an X-RAY imaging machine. Some researched existing used Covid-Chest X-ray-Dataset (D. B. Mule, S. S. Chowhan, and D. R. Somwanshi, 2019) and Chest X-Ray Images (Pneumonia) from Kaggle repository (L. Perez and J. Wang, 2017). The Table.2 shows each frontal pneumonia CXR by type and genus or species, if appropriate. The composition of the hierarchy is shown from left to right on the map. Information is gathered for reference to a verified test by manually reading clinical notes (D. B. Mule, S. S. Chowhan, and D. R. Somwanshi, 2019). X-Ray images of different people with COVID- 19 and a person (normal) are shown in Fig2.

Table 2 CXR Type

Type	Genus or Species	Image Count
Viral	COVID-19 (SARSr-CoV-2)	434
	SARS (SARSr-CoV-1)	16
	Varicella	4
	Influenza	1
Bacterial	*Streptococcus* spp.	13
	Klebsiella spp.	7
	Escherichia coli	4
	Mycoplasma spp.	4
	Legionella spp.	4
	Unknown	2
	Chlamydophila spp.	1
Fungal	*Pneumocystis* spp.	13
Lipoid	Non applicable	3
Unknown	Unknown	13

Sample Chest X-Ray

2. **CT images sources:** Computed tomography (CT) provides more details than an X-ray. However, the use of CT images makes the detection of COVID-19 construction of the model convenient. The datasets such as Covid-CT DATABASE, MedSeg, and Covid-CT DATABASE contain hundreds of axial CT images. CT images of different people with normal and COVID-19 case is shown in Fig. 3.

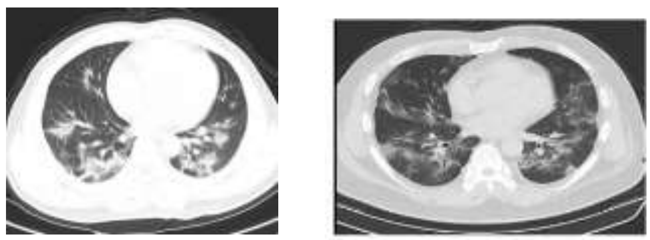

Figure 3. Sample CT Type

3. Pre-Processing Techniques

More COVID-19 datasets are built with some obscure, duplicate, and blur types of image data items. For this reason, the performance of the model degrades without using clearly defined images. There are many approaches to pre-processing techniques based on datasets. Also, one of the real problems in deep learning is overfitting and an element of imbalance. Solving this problem used data augmentations by either data warping or oversampling. For example, data warping augmentations transform current images. Their label is preserved, like flipping or distorting the input image, adding a small amount of noise, or cropping a patch from a random position (L. Perez and J. Wang, 2017) (R. Takahashi, T. Matsubara, and K. Uehara, 2020).

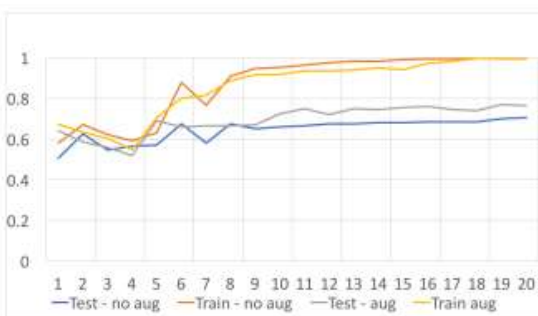

Figure 4: Precision plot for training

The Figure 4 above shows a precision plot at each epoch that neural augmentation helps prevent overfitting. Training accuracy with augmentation is slightly lower than training accuracy without increasing most of the first 20 training epochs. Increased learning appears to generalize the classifier (R. Takahashi, T. Matsubara, and K. Uehara, 2020). On the other hand, Generative Adversarial Networks (GANs) create synthetic instances and add them to the training set, such as mixing images, feature space augmentations. GAN is a smart model that creates synthetic images. It is a powerful way to produce uncontrolled samples with a min-max game. The general principle of GANs is to use two opposing networks (G(z) and D(x) where one (G(z) generator generates a logical image for a network better suited to distinguish between true and false images (D(z) discriminator). The generator's goal is to minimize the cost value function of V(D, G) while the discriminator maximizes it (Y. Jiang, H. Chen, M. H. Loew, and H. Ko, 2020).

This section has adopted dataset augmentation techniques that have used augmented data to improve image detection performance. The most pre-processing and data augmentation used are:

A. Rotating and Flipping: to increase the sample and enhance dataset size, the images can be turned in many angles, such as 90º, 180o, and 270º (P. Q. Le, A. M. Iliyasu, F. Dong, and K. Hirota, 2010).

B. Scaling or cropping: the second augmentation used is achieved by resampling images such that the scale of whole images shifts. Scaling can enlarge or lessen an image in size. Cropping decreased redundancy on different scales and shrink unnecessary regions (P. Q. Le, A. M. Iliyasu, F. Dong, and K. Hirota, 2010) (M. Alghoniemy and A. H. Tewfik, 2004).

C. Brightness or intensity : is adjusting to increase or reduce the brightness of images by substituting pixel values with a constant (M. Alghoniemy and A. H. Tewfik, 2004).

3. Machine Learning Techniques

Machine learning (ML) is a branch of computer sciences that has been rapidly and increasingly find applications in many fields, such as malware detection. Malware has been a great threat to computer systems these days (M. Alazab, at al 2012). ML has been used in medicine (Y. Xu, at al, 2018) and natural language processing (T. Young, D. Hazarika, S. Poria, and E. Cambria, 2018). However, Deep Learning (DL) is a subcategory of machine learning inspired by artificial neural networks, commonly known as ANN (M. Z. Alom *et al.*, 2018).DL enables computational models to contain multiple processing layers to learn data representations through many layers. The most common techniques used in detecting COVID-19 from medical images: Convolutional networks (CNN), Transfer learning models in DL, and Generative Adversarial Networks. (D. Singh, et al 2020). Studies that mammograms excluded ROIs containing biopsy or natural tissue. CNN had an input layer, two hidden layers, an output layer. Training time was described as "computer-intensive," in this pre-GPU period, but no time was given. CNN was used to detect lung nodule A CNN in 1995 to detect microcalcification mammography.

Level 1:

For input signal X (image) and kernel K, the two-dimensional convolution operation can be defined as follows:
$(X * K)(i,j) = \sum_m \sum_n k(m,n)X(i-m,j-n)$

X represents the input image matrix to be transformed into a new (X*K) matrix representing the output image with kernel matrix (X*K). The i and j indices here deal with the image matrixes, while the m and n indices deal with the kernel indices. If the size of the convolution kernel is 3 * 3, the indices m and n range from-1 to 1. [9].

Level 2:

It is the most established among various deep learning models and a class of artificial neural network. In

(D. Singh, et al 2020), the authors have used CNN to classify patients with COVID-19 as infected (+ve) or not (-ve).   The Fig. 6, shows the proposed and competitive classification models ROC obtained. It clearly shows that the proposed model achieves good results relative to competing models. Accuracy is determined by dividing classes explicitly identified by total class number.

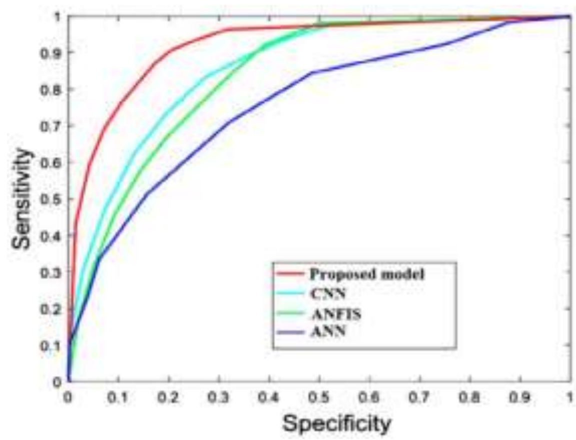

Figure 4: ROC obtained

The CNN initial parameters are tuned using multi-target differential evolution (MODE). The proposed model and competitive machine learning techniques on chest CT images, through comprehensive analysis, can classify chest CT images with good accuracy. The proposed deep learning model has been designed using differential multi-target development (MODE) and convolutional neural networks (CNN) to classify humans affected by COVID-19. CNN meta-parameters are optimized with the MODE algorithm. The proposed model is trained by looking at chest CT images of COVID-19 patients. And a procedure between MODE-based CNN and competitive models such as Convolutional Neural Networks (CNN), Adaptive Fuzzy Neural Inference Systems (ANFIS), and Artificial Neural Networks (ANN) by looking at well-known classification scales. Large-scale experimental results have been recorded which have shown that the proposed model outperforms the competitive models of ANN, ANFIS, and CNN models in terms of accuracy, F-measurement, sensitivity, specificity, and kappa statistics by 1.9789%, 2.0928%, 1.8262%, 1.6827%, and 1.9276%. Respectively. Therefore, the study has concluded that the proposed model is useful for real-time classification of COVID-19 disease from chest CT images.

Besides, in (Y.-H. Wu *et al.*, 2020), the authors have produced two main contributions: 1- Building a new large-scale COVID-19 dataset, called COVID-CS, which contains 3,855 micro-CT scans, labeled with CT scans from 200 patients, and 64,771 patient-level annotated CT images from 200 COVID-19 patients and 75,541 cross-sectional images of 350 uninfected cases, 2- Developing a new diagnostic system for COVID-19 to conduct Joint Interpretable Classification and Micro Pest Segmentation (JCS), which have shown clear superiority over previous systems.

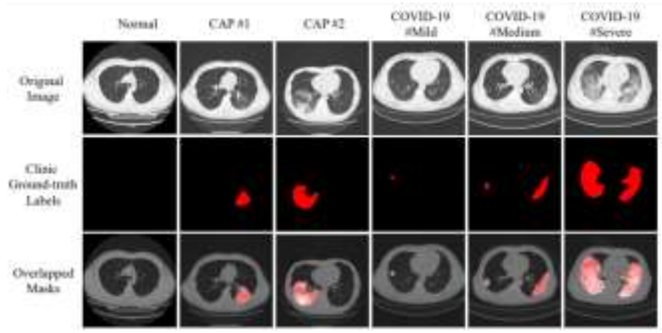

Figure 5: CT Images Dataset.

The Figure 5 above show example of COVID-CS dataset they used , including CT scan images and labels of a normal person (1 st column), two community-acquired pneumonia (CAP) cases (2nd and 3rd columns), and three COVID-19 patients from mild to severe (X. Wu *et al.*, 2019).

The proposed segmentation model aims to discover accurate areas of infection from CT images of COVID-19 patients. The form consists of

- Encoder Engineering - Decoder: The hash model consists of an encoder and a decoder. Encryption. The encoder is based on the VGG-16 backbone. It has five containing five VGG blocks identified as E1, E2, E3, E4, and E5.
- Enhanced Features Module: the proposed EFM has been added after the last layer of E5 in the VGG-16 encoder.

The pattern classification results have been good under different thresholds in the test group for the COVID-CS dataset, achieving a sensitivity of 95.0% and 93.0% specificity at the threshold of 25. However, AM has been unable to provide an accurate segmentation of lesion regions in an organ or tissue undergoing damage as a result of the COVID-19. The authors have implemented a segmentation model to detect subtle lesion regions in CT images of COVID-19 patients. Compared to competing methods, for example, PoolNet, the proposed hash model has improved at 0.078 on the dice scale.

Through reference (C. Butt, et al, 2020), the authors technically review a study that has compared multiple convolutional neural network (CNN) models for classifying CT samples with COVID-19, influenza viral pneumonia, or no infection, and worked to develop deep learning models, integrating them with the latest clinical understanding. Dataset: 618 cross-sectional samples have been collected in this study, including 219 from 110 patients with COVID-19. The cross-sectional 528 samples (85.4%) have been used for training, including those with COVID-19, patients with influenza 'A' viral pneumonia, and samples from healthy people. Residual 90 CT groups (14.6%) have been used as the test group. As a result, ResNet has been used to extract features from CT images. It can accurately distinguish COVID-19 cases from other cases; the study has achieved an AUC of 0.996 (95% CI: 0.989-1.00) for Coronavirus cases versus non-Coronavirus for all CT studies.

The purpose of this paper (X. Wu *et al.*, 2019) has been to develop a deep learning-based method for the rapid and accurate identification of COVID-19 patients utilizing CT images collected of 495 patients from three hospitals in China, and 495 data sets have been randomly divided into 395 cases (80%, 294 from COVID-19, 101 from other pneumonia) from the training set, and 50 cases (10%, 37 from COVID-19, 13 from other pneumonia) from Validation group and 50 cases (10%, 37 cases of

COVID-19, 13 other pneumonia cases) from the test group. The authors have been trained a multi-vision fusion model using a deep learning network to screen those with COVID-19 using CT images through the distal lung regions, axial, coronal, and sagittal views. The performance of the proposed model has been evaluated through the verification and testing groups. The proposed model (AUC) of 0.732, an accuracy of 0.700, a sensitivity of 0.730, and a specificity of 0.615 has achieved the validation set. In the test set, they achieve AUC, accuracy, sensitivity, and specificity of 0.819, 0.760, 0.811, and 0.615, respectively. The proposed diagnostic model based on the deep learning method has shown great potential for improving diagnostic efficacy and relieving the radiologists of the burden for initial COVID-19 pneumonia screening.

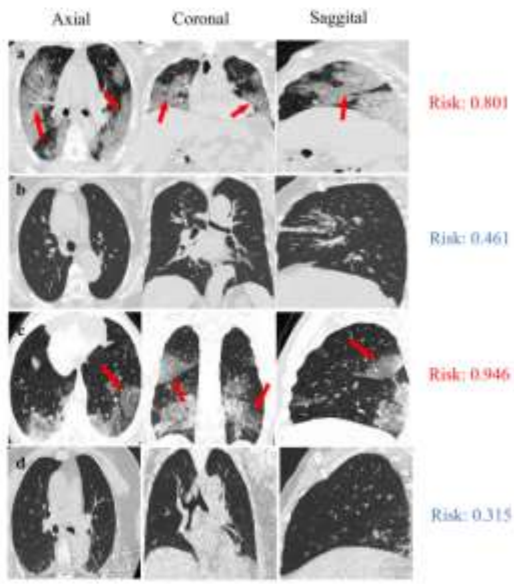

Figure 6: CT images of pneumonia diagnosis

The Figure 6 above has examples of pneumonia diagnosis for a 46-year-old male with COVID-19 pneumonia (a), an 84-year-old female with bacterial pneumonia in validation set (b), a 62-year-old male with COVID-19 pneumonia (c) and a 52-year-old female with bacterial pneumonia in testing set (d). The risk scores of these four patients with COVID-19 infections are 0.801, 0.461, 0.946, and 0.315 (range from 0 to 1), respectively, assessed by the multi-view deep learning fusion model. The cut-off of the model is 0.653. The ground-glass opacity in COVID-19 patients is marked with red arrows (a, c) (X. Wu *et al.*, 2019)

Level 3: Transfer learning Models

Pre-trained models are ML (H. C. Shin *et al.*, 2016), which has already been trained to address a specific problem. It is based on the concept of reusability transfer learning usually used with CNN. Moreover, weight and bias in transfer learning are transferred from large-scale train models to similar testing and retraining (M. Z. Alom *et al.*, 2018). For medical applications, this technique can be particularly important because it does not require much training data and because it is difficult to obtain data in the medical field. Researchers' main challenges in medical care related to obtaining reliable data are that a small or limited number of datasets are available under normal conditions. However, deep learning needs many data to train models from scratch, so labeling this data takes more time and high computing power. There are several pre-trained models used for in detection of the COVID-19 field.

In (M. Loey, G. Manogaran, and N. E. M. Khalifa, 2020) the key motivation is limited to COVID-19 benchmark datasets, particularly in the chest CT image. The key concept is to collect all potential COVID-19 photos that remain until this research is released, using traditional data increases, and CGAN generates additional photos to help detect COVID-19. Five separate profoundly coevolutionary, network-based models were chosen to detect infected patients with chest CT digital radiographs (AlexNet, VGGNet16, VGGNet19, Google Net, and ResNet50). Classical data and CGAN boost classification efficiency in all selected deep transfer models. Results show that ResNet50 is the most powerful deep learning model for detecting COVID-19 from restricted chest CT data with an 82.91% classical data increase, 77.66% sensitivity, and 87.62% speciality.

In (A. Narin, C. Kaya, and Z. Pamuk, 2020), the authors have aimed to establish an automatic detection system as an alternative and rapid diagnostic option to prevent the spread of COVID-19 disease among people. The proposed models are based on three convolutional neural networks (ResNet50, InceptionV3, and Inception- ResNetV2) to detect the medical condition of COVID-19 patients. A person with coronary pneumonia is detected by using a chest X-ray. The ROC and confusion matrices are analyzed by these three models, using 5-fold validation. The research has indicated that the pre-trained ResNet50 model's performance results provide the highest classification performance with 98% accuracy compared to the other two proposed models of 97% accuracy for InceptionV3 and 87% accuracy for Inception-ResNetV2. The datasets have been obtained to representing chest X-rays of 50 patients from COVID-19 from the open-source repository of GitHub. This repository consists of chest X-ray/CT images of patients who mainly suffer from acute respiratory distress syndrome (ARDS), COVID-19, Middle East respiratory syndrome (MERS), pneumonia, and Severe Acute Respiratory Syndrome (SARS). The paper indicates the best performance of 98% accuracy, 96% recall, and a specificity value of 100% for a pre-trained ResNet50 model. The lowest performance values have been obtained with 87% accuracy, a recall of 84%, and a specificity of 90% for Inception-ResNetV2. Based on these results, the ResNet50 model outperforms the other two models in the training and testing phase.

In (S. Minaee, at al 2020), the authors have provided models for training four common convolutional neural networks, including ResNet18, ResNet50, SqueezeNet, and DenseNet-121, to identify COVID-19 disease in the analyzed chest X-ray images. They have evaluated these models on 3,000 images, and most of them have achieved a sensitivity ratio of 98% (+ -3%), with a privacy rate of close to 90%. Besides sensitivity and specificity rates, they also have provided a receiver operating characteristic (ROC) curve, exact retrieval curve, mean prediction, and confusion matrix for each model. The technology is also used to create heat maps of lung areas likely to be infected with the COVID-19 virus, which has shown these maps on most affected areas with our certified radiologists' knowledge. Two strategies have been adopted to address the COVID-19 image problem:

1) Used augmented data to create a converted version of the COVID-19 images through flipping, small rotation, and adding a small number of distortions to increase the number of samples.
2) Instead of training these models from scratch, the last layer of a pre-trained version of these models is set to ImageNet.

In this way, the model can be trained using lower-rated samples derived from each class. As a

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result, the best performing model has achieved a 98% sensitivity, with 92% specificity. Using deep visualization technology has provided heat maps of the most likely areas with Covid-19 and made the data set, trained models, and implementation available to the public.

The paper from (I. D. Apostolopoulos and T. A. Mpesiana, 2020) has presented an automatic detection method for Covid-19 disease. A dataset based on X-ray images from patients with common bacterial pneumonia has been used. The goal has been to evaluate the performance of the latest convolutional neural network structures.

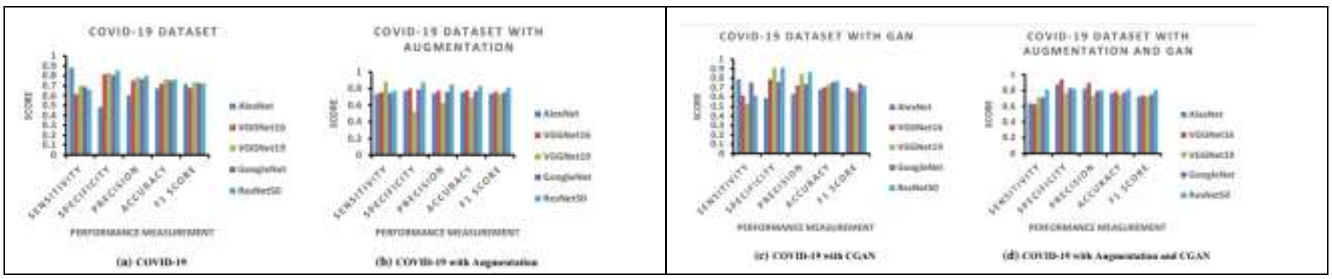

Figure 9: Performance metrics of CT datasets

The above pictures present the performance metrics for the COVID-19 CT dataset for various scenarios with DTL models. The overall 88.3 percent sensitivity. Moreover, it indicates that several X-ray sources have been accessed. First: from analyzing the Github repository of relevant datasets, a set of X-ray images have been chosen from Cohen [4]. Second: from the sites of Radiological Society of North America (RSNA), Adiopaedia and Italian Society of Medical and Interventional Radiology (SIRM). Third: a common pneumonia x-ray assay kit to train CNNs to distinguish between Covid-19 and common pneumonia. Training and evaluation have been conducted, providing accuracy, sensitivity, and specificity. The results indicate that VGG19 and MobileNetV2 achieve the best rating accuracy over the other categories of CNNs.

In this paper (M. Farooq and A. Hafeez, 2020), the authors have used state-of-the-art training techniques, including progressive scaling and finding cyclic learning rates and discriminatory learning rates, to quickly and accurately train the remaining neural networks. To detect subjects suffering from COVID-19 during an open-access dataset. This paper has provided a 3-step technique for tuning a pre-trained ResNet-50 architecture to optimize model performance and reduce training time developing into what is referred to as COVID-ResNet. This is achieved through progressive resizing of the input images and fine-tuning of the network at each stage. With this approach, one can achieve an accuracy status of 96.23% across all categories on the COVIDx dataset with only 41 historically kept epochs' datasets. This model has been able to assist in the early screening of COVID-19 cases. It has provided a highly efficient and highly accurate computational model for multi-class classification of three different types of infections from normal individuals.

Moreover, the authors in (L. Wang, Z. Q. Lin, and A. Wong, 2020) aim to build open-source accessible filtering to help fight the COVID-19 pandemic, using the neural network architecture model known as COVID-Net, which uses the COVIDx dataset. This model has reported an accuracy of 83.5% in total. This paper has used the same data set for the following purposes: to improve the overall model resolution for all groups with positive predictive values > 90, to use a network architecture with fewer parameters and minimum computational requirements and the use of techniques for training models that need fewer times and faster training.

The authors have relied on Data Augmentation for images in the proposed model that help generate more recent examples by randomly transforming training images. The conversion has included vertical fluctuations of the training images, random rotation of images, and lighting conditions. Data Augmentation increases the volume of input training data, thus improving the generalizability of the training model. Data Augmentation has been only like for training, and increased testing time has not been explored. The paper has used a variant of the remaining neural network for a total of 50 layers called ResNet50. It has led to faster training. Also, the ability to feed images of sizes other than the one they are trained in. This is an essential part of the training exercise of a high-performance network with very little interval using the technologies introduced in Fast.ai. Also, while comparing the resulting network COVID-ResNet to the original results on the COVIDx dataset, the authors have achieved a significant performance improvement and 13% (96.23% compared to 83.5% in COVID-Net) with 4.5 time's lower parameters (25.6 million versus 116.6 million COVID-Net).

In (E. E.-D. Hemdan, M. A. Shouman, and M. E. Karar, 2020), the authors completely build deep learning models into a new framework (COVIDX-Net) to automatically help diagnose patients with COVID-19B and to achieve the proposed experimental analysis deep learning image classifiers in the COVID-19 disease classification task using chest radiographs. The traditional imaging method has a lower cost than other imaging methods such as computed tomography. It also supports the proposed COVIDX-Net framework to develop AI technologies further to fight the COVID-19. The authors have proposed a new deep learning framework for COVIDX-Net, building on seven different DCNN architectures of VGG19, DenseNet201, InceptionV3, ResNetV2, InceptionResNetV2, Xception, and MobileNetV2. The available dataset of X-ray images has been used in this study to classify negative and positive COVID-19, provided by Dr. Joseph Cohen and Dr. Adrian Rosebrook2. The dataset includes 50 X-ray images, divided into 25 normal and 25 images of Positive cases for COVID-19. For the experimental setup, all the images have been resized to 224 x 224 pixels.

The COVIDX-Net framework, including deep learning classifiers, has been implemented using Python and the Keras package with TensorFlow2. The resulting test times of the COVIDX-Net models do not exceed 6 seconds on ten images under test. The accuracy of the InceptionV3 model has been the worst at 50%, while the VGG19 and DenseNet201 models have achieved the best accuracy values (90%). Although the MobileNetV2 model has shown a moderate value of accuracy (60%), it has achieved the shortest computational time of 389.0 and 1.0 seconds.

The authors in (T. Ozturk, et al. 2020) have researched to deploy the developed model in helping radiologists validate their initial screening. Instead of initiating a deep model development from scratch, the researched designed DN (DarkNe) architecture, which is a classifier model that forms the basis of a real-time object detection system named YOLO standing for 'You Only Look Once', which has proved deep learning by itself, instead of constructing a platform from scratch. However, the Darknet-19 basics consist of 19 convolutional layers and five pooling layers, using Maxpool. Similarity CNN layers with different filter numbers, sizes, and values stride. Using fewer layers and filters than original DarkNet architecture and the number of filters gradually increased to 8, 16, and 32. The proposed model's architecture contains 17 convolution layers; there is one convolution layer for each DN layer, followed by BatchNorm and LeakyReLU operations. The Maxpool method has been used in all the pooling operations. The model also has developed using raw chest X-ray images of 127 infected patients with 500 no-findings and 500 records of pneumonia cases, which has achieved a performance, 98.08% for binary class and 87.02% for multi-class. Multi-classes have proved the expert system's applicability to help radiology in timely and reliable validation of the screening process.

In (F. Ucar and D. Korkmaz, 2019), the authors propose a specifically designed deep learning model called COVIDiagnosis-Net, which is an AI detection approach based on deep SqueezeNet with Bayes optimization. SqueezeNet is a pre-trained CNN model that achieves AlexNet-level accuracy on ImageNet with 50x fewer parameters. Furthermore, the CNN network is optimized with the Bayesian-based method, a sequential design strategy, during training.

Comparison	Params (M)	Training Epochs	Accuracy (%)
COVID-ResNet	25.6	41	96.23
COVID-Net	116.6	100	83.5

Table 2. Sensitivity of each class

Recall (Sensitivity) %			
Normal	Bacterial	Viral	COVID-19
96.58	97.15	93.96	100.0

Table 3. Precision (Positive Predictive Value) of each class

Positive Predictive Value (Precision) %			
Normal	Bacterial	Viral	COVID-19
99.12	95.60	92.72	100.0

Table 3. F1-score of each class

F-1 score %			
Normal	Bacterial	Viral	COVID-19
97.84	96.37	93.33	100.0

Table 2: Performance of COVID-ResNet on COVIDx test dataset (M. Farooq and A. Hafeez, 2020).

The SqueezeNet consists of fifteen layers and five different layers as two convolution layers, three max-pooling layers, eight fire layers, one global average pooling layer, and one output layer softmax. Due to the size of the images is not equal, using multi-scale augmentation process in pre-processing steps is to address the imbalance problem of the public dataset proposed. Firstly, by flipping each image to be a mirrored version of the original images.

Then the applied augmentation techniques including noise, shear, brightness decrease, and brightness increase for both original and flipped images. Moreover, the offline augmentation method is utilized on the raw input X-ray images. However, for smaller classes with fewer sample numbers, this method is recommended to increase the size of the classes by a factor of transformation. For the dataset is divided into three packages as training, validation, and test sets after pre-processing 80% for training, 10% for validation, and 10% for testing. Training and validation datasets are designed for Bayesian optimization, which is based on online learning structure.

Level 4: Generative Adversarial Networks

A further in-depth study such as (A. Waheed, et al. 2020) (T. Goel, et al. 2021) has been applied Generative Adversarial Networks GANs to generate new samples after being trained on samples drawn from some distribution in training sets.

In ((T. Goel, et al. 2021) used GAN to generate more CT images, The GAN hyperparameter generator is optimized using the Whale Optimization Algorithm (WOA) is used to optimize the hyperparameters of GAN's generator to avoid overfitting and instability issues. The dataset used called SARS-CoV-2 CT-Scan dataset, consisting of COVID-19 and non-COVID-19 images. The performance metrics which has achieved , including accuracy (99.22%), sensitivity (99.78%), specificity (97.78%), F1-score (98.79%).

In (A. Waheed, et al. 2020) the proposed technique to produce X-ray (CXR) images by Auxiliary Classifier Generative Adversarial Network (ACGAN) based model called CovidGAN, for COVID- 19 detection, a VGG16 network is used. The datasets used are obtained by a combination of various datasets from three publicly available datasets comprising 1124 CXR images, 403 COVID-CXR images, and 721 Normal-CXR images. The limited number of cases for CXR images of COVID-19 that indicate the limited availability of public domain COVID-19 data. Therefore, authors using CovidGAN for augmentation of the training dataset. Generative Adversarial Networks (GANs) uses two neural networks competing to build new virtual data instances that can be transmitted as real data using the GAN version called Auxiliary Classifier GAN to achieve data augmentation. Classification using CNN alone has resulted in 85%, whereas the accuracy has improved by adding synthetic images created by CovidGAN to 95%.

4. Discussion

The research objectives have reviewed that diagnostic methods play a key role in the management of infectious diseases and pandemic disorders, such as the COVID-19. Some shortcomings of the RT-PCR nucleic acid test modules suggest the need for rapid alternative methods such that front-line experts can be diagnosed rapidly and reliably. The suggested method for diagnosing pneumonia shows approximately 87.26% accuracy of the studies in other papers, while the recently published paper shows 84.67% accuracy in (A. Waheed, et al. 2020)

This review paper gives an overview of previous papers where the results are obtained by detecting COVID-19 based on medical images. This section has presented some consideration of techniques being used in the detection, modality, and size of the used datasets. Some papers have used to assess the model's reliability by adopting some matrices to show how the results are achieved in terms of parameters such as precision, recall, and the F-measure, etc.

The techniques used in the reviewed papers for the detection of COVID-19 have been in Machine Learning (ML). The most commonly used is referred to as Transfer learning models, which give promising results. Most ML algorithms have shown almost similar results in evaluating metrics used to evaluate algorithm performance. It is hard to determine on deciding on the best techniques; hence there are different modality and limited datasets. The dataset has varied based on modality. Most of the paper's detection used X-ray images rather than CT images due to faster, simpler, cheaper availability of X-ray data, as almost all hospitals have X-ray imaging machines.

5. Conclusion and Future Research

We have focused on analyzing the techniques used in the detection COVID-19 and the variation, type, and size of the dataset. Also, the results have been achieved in the detection COVID-19 and discussed in detail and obtained some consideration. Moreover, it is shown that the research area of medical images in detection has been richly populated with different techniques and datasets with many research opportunities to achieve an efficient solution to checking the spread of the COVID-19.

This paper encourages future works in-field detection of COVID-19 based on medical images. There is a shortage of medical images of COVID-19 for the infected patient, for playing an essential role in enhancing the models. Although this review paper does not claim to be a depth reflection on these papers, it provides a realistic viewpoint and demonstrates a valid comparison over these months. Also, this review can be the guide for the researchers to find the future direction.

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