A Review of Preprocessing Methods and Pre-Trained Models for COVID-19 Detection using Medical Images

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***Abstract*— Huge number of people have died due to the outbreak of the Pandemic of the COVID-19 virus. The virus inflamed millions of humans, and the inflammation continues each day. The detection of the severity of COVID-19 among sufferers at an early stage is a critical component of preventing the disorder. As of today, the only way to detect COVID-19 is through reverse transcription polymerase chain reaction (RTPCR)based detection of the Viral nucleic acids; however, this method is not a very sensitive technique[1]. In the absence of RT-PCR or in the case of a negative result in symptomatic COVID-19 cases, chest imaging is considered part of the screening procedure[2]. Using CT or X-ray images of the lung, this paper reviewed some of the newly emerging Deep Learning models that are capable of capturing COVID-19 using medical images. Obtaining data on research resources and inspecting around 20 papers from the period of 2019 to 2021. Deep learning-based frameworks, data analysis, preprocessing approaches, and feature extraction may be beneficial in establishing the direction of study in the field of automated diagnosis of Covid19 illness.**

Keywords—: COVID-19; Deep Learning; Medical Image

I. INTRODUCTION

The most common causes of coronavirus infections are SARS (severe acute respiratory syndrome) and Middle East respiratory syndrome (MERS). SARSCoV2 causes an infection called COVID19, which is caused by a novel coronavirus. COVID-19 was first detected in Wuhan, Hubei Province, China, in December 2019 [3].On March 11, 2021, the World Health Organization declared COVID19 a pandemic. Breathing issues are caused by various conditions, which can be treated without the need for specific medications or equipment. However, fundamental medical conditions such diabetic, cancer, coronary heart disease, and respiratory illness might exacerbate the disease. The major approaches for COVID19 detection are reverse polymerase chain reaction (RT-PCR) and gene sequencing for respiratory or blood samples (4). According to other studies, COVID19 has a medical condition similar to that found in lung disease, and the chest condition remains visible on medical images.

There is still much to learn about this disease in humans as it is not yet able to fully determine the etiology of this disease.An infection presents with nonspecific symptoms, such as cough, respiratory symptoms, wheezing, and high fever [5].Due to a lack of nucleic acid detection boxes and low detection rates in the epidemic area, diagnosis has become a growing challenge in many hospitals with the daily increase in the number of suspected and newly diagnosed cases[6].

Computer tomography (CT) is perhaps a better and more reliable, practical, faster and time-efficient method of categorizing and assessing COVID19 than RTPCR, especially in the epidemic region[7]. CT image screening is available in almost all hospitals, therefore thorax CT images can be utilised to discover COVID19 patients in early stages itself. On the other hand, Thorax CT-based COVID19 classification requires the input of a radiology expertise, and which wastes a lot of precious time. Currently, it takes more than 24 hours for the COVID19 test results to identify the virus in the human body.It is critical to diagnose the sickness early on and place those who are affected under quarantine as soon as possible. According to Chinese regulators, the RTPCR methodology is effective for diagnosis and confirmation of the COVID19. As a result of high false-negative rates and the time commitment associated with the machine used for the test, COVID19 is a difficult pathogen to identify and diagnose. Computerized tomography and radiography have been deemed as integral tools in the identification and diagnosis of COVID19 [8].

However, there were many patients and few radiologists resulted high percentage of false-positive rates [8]. Additionally, the availability of RTPCR is limited in many regions of the world. Therefore, computed tomography (CT) images and X-rays may be the suboptimal method for detecting the COVID19. It is feasible to use a CT scan or X-ray imaging if RTPCR can't be performed. Besides, the RTPCR takes a great deal of time and money. Also, the collection of samples for PCR requires proper training. On the other hand, CT images and X-rays are relatively easy to work with. An advanced computerized lung diagnostic method is urgently needed to accurately identify suspected patients, screen patients, and conduct virus surveillance.

In the medical field, deep learning has proven to be the most effective way of diagnosing and predicting many types of diseases more accurately than ever before. Artificial intelligence is rapidly becoming a valuable tool for medical imaging as proven by research on deep learning. With the rapid development of artificial intelligence (AI), computer vision technology, which originally classifies general images, is being applied to medical images including images from CT scans and X-rays.

II. LITERATURE REVIEW

Researchers have carried out many studies and research in the area of diagnostics from medical images, including computer tomography scans and X-ray images using AI and deep learning. This survey will cover many research papers relating to COVID19 identification from medical images and related works. The major goal of this study is to properly explain existing research workflows so that fresh researchers may examine earlier work and come up with a superior answer. This work focuses on the approach, which includes data preprocessing, augmentation strategies, and how to extract features from augmented data.

A. Preprocessing Techniques

The purpose of preprocessing is to increase the quality of the image so that it can be analyzed better. Preprocessing can reduce unwanted distortion and improve some of the characteristics required for a particular task. Overfitting is the main difficulty with deep learning.Data augmentation is employed in the pre-processing step to mitigate the effect of overfitting. The most common data augmentation techniques include resizing, scaling, cropping, flipping, and rotating. The following are some examples of data augmentation techniques:

i) Resizing: Due to the different sizes of the images, resizing is a crucial step as the preparation of the model is made more difficult by the differences. To make the dataset more universal, all of the images are resized to a given dimension, such as 224 x 224 or 299 x 299[9].

ii) Flipping or Rotating: This method improves sample size for datasets. The usage of horizontal and vertical axis flipping is common.

iii) Scaling or Cropping: It is the second most popular procedure for augmentation. The usage of entire sections of the images is not necessary. As a result, the cropping approach was utilized by researchers to reduce duplication.

iv) Brightness or Intensity adjusting: In order to make an analysis more effective, it is vital to increase and decrease the image’s brightness.

v) General Adversarial Network (GAN): It is the technique of using deep learning technologies to do Generative modelling. This unsupervised learning algorithm uncovers patterns, similarities, and patterns within an input dataset and then generates data that is close to the input dataset. However, GAN[10] does not ensure the quality of the samples, although it increases the sample size.

B. Feature Extraction Methods

The extraction of features is a key step for classification because the extracted features describe the relevant properties of the images. When it comes to image feature extraction, Deep Neural Networks (DNN) perform particularly well. As a consequence, they're commonly employed in Computer Vision Algorithms and Convolutional Neural Networks.

Deep learning algorithms such as convolutional neural networks take input images, assign weights and biases (learnables) to distinct aspects or objects, and distinguish them from each other. In comparison to several algorithms of classification, CNN requires far less pre-processing. The important part of the primitive techniques is to create filtering by hand, but CNNs can learn these properties and filters with enough training. Here are some examples of pre-trained models of CNN:

i) Residual Network (ResNet)

ResNet is an architecture for convolutional neural networks (CNNs) that allows multiple layers to be used. ResNet [11] may add a great number of layers with a high performance, whereas prior CNN designs hindered the efficacy of additional layers. Data-driven, user-friendly and efficient system is what ResidualNet offers.There are many variations (ResNet18, ResNet169,ResNet50, ResNet152, etc.) and this network's image input size is 224x224 pixels.

ii) Densely Connected Convolutional Networks (DenseNet)

In recent years, DenseNet has proven itself to be among the most effective methods for visual object detection[12]. Essentially it is the same as ResNet, but there are some important differences. In order to ensure maximal information flow between the network layers, the architecture is very simple. As the feature map was sized across the network, we connected each layer straight to all levels after that, the Densely Connected Neural Network, or just what we call DenseNet. By presenting these unique network architectures, it created the data flow between layers. Disparate several other networks, including ResNet, DenseNets concatenates the output feature maps of the layer with the input feature map rather than summating them.There are various types of variants of this architecture (DenseNet101, DenseNet169, DenseNet201) that use 224x224 pixels as inputs.

iii) Visual Geometric Group (VGG)

VGG[13] is an advanced multi-layer deep Convolutional Neural Network(CNN) architecture. VGG16 and VGG19 each comprise 16 and 19 convolutional layers. The "depth" indicates the number of layers.224 x 224 pixels are the dimensions of the input image. In order to modify the decision function further nonlinear, VGG integrates 1x1 convolutional layers while keeping the receptive fields unchanged.

iv) Inception

The concept of inception is a prominent transfer learning-based approach among researchers[14] [15]. Two parts of it are used: feature extraction from images using CNN, followed by classification using the Softmax and fully linked layers. Inception has a lot of different variations.InceptionV1, InceptionV2, InceptionV3, and InceptionV4 are among the most popular. As part of this architecture, the input image dimension is 299 x 299 pixels.

C. Validation Criteria

The researchers mainly used a measure of precision, recall, F1-score and accuracy to validate the proposed approach.

These measures are calculated based on the following formulas:

$$\text{Accuracy} = \frac{TP + TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{FN+TP} \quad (3)$$

$$\text{F1-Score} = \frac{\text{Precision} + \text{Recall}}{2} \quad (4)$$

III COMPARISON WITH RELATED WORKS

Kamel et al [16] VGGNet 19, a famous CNN architecture that has previously been trained on ImageNet, was used to extract feature information from the preprocessed CT images. As a result, the suggested pipeline performs extremely well with scores of 98.31%, 100%, 98.19%, and 98.64% for accuracy, recall, precision, and F1-score, respectively. The main research gap of this paper is the usage of limited datasets and it considered only CT-scan datasets.

Song, Ying, et al [17] used the ResNet model for the COVID-19 detection. In this study, the authors developed a deep learning-based CT diagnosis system based on data collected from 88 patients with COVID19 in two Chinese regions. Based on these data, the authors identified patients who had COVID19 using chest CT scans. Results from the experiment show an AUC, recall (sensitivity) and a precision of 0.95, 0.96, and 0.79 respectively. In this paper, the most significant research gap is the problem with the dataset as this work is achieved at the very beginning stage of the COVID pandemic.

Table 1. Comparison with other related work

Author	CNN Architectures	Image Classification	Image Type	Total Dataset	Accuracy
Shah, Vriddhi, et al [19]	VGG-19	COVID-19 positive and COVID-19 negative	CT-scan	738	94.52 %
Shelke et al. [20]	DenseNet-161	COVID-19 and pneumonia	X-ray	COVID-19: 500 Pneumonia: 500	98.9 %
Jain et al. [21]	ResNet-101	COVID-19 and viral pneumonia	X-ray	COVID-19: 440 Viral pneumonia: 480	97.78 %
Song, Ying, et al [17]	DRE-Net	COVID-19, Bacterial, Healthy	CT-scan	COVID-19: 777 Healthy:708 Bacterial pneumonia:505	93%

Sitaula et al [18] in this paper, authors used a unique attention module with VGG16 to construct a novel attention-based deep learning model. In CXR images, the attention module derives the spatial relationship between ROIs based on the spatial relationship between them. Additionally, by incorporating the attention module in the VGG-16 model, a novel deep learning model was developed that incorporated an appropriate convolution layer (4th pooling layer) to adjust the classification process accordingly. There is a research gap in this paper because none of the offline data augmentation techniques are used in the experiment. Furthermore, intensive augmentation techniques, such as GANs or Convolutional Auto-encoders, could improve the performance further.

Shah, Vriddhi, et al [19] proposed CTnet-10 which is a self-developed model with an accuracy of 94.52 percent, was built for the COVID-19 diagnostic. The research gap of this paper is it does not differentiate between COVID pneumonia and bacterial pneumonia and it only considered CT scan images.

IV CONCLUSION

With the rapid spread of COVID19 around the world, the ability to detect threats accurately and rapidly has become crucial. In this paper, we sought to provide a thorough examination of deep learning methods for addressing the pandemic challenges of COVID19 using medical images by detecting them relatively quickly at a low cost. This paper examined a variety of COVID19 diagnostic models, including the use of CT images and X-rays. From this overview, we can observe that, the X-ray image dataset can be found more readily than the CT image dataset since CT scans are more expensive and time consuming. Therefore, majority of the researchers used chest X-ray images to diagnose COVID19. The main research gap in the papers is a problem with the dataset. And most of the papers only concentrate on either CT or X-ray images. So need to develop a system that accepts both images and predicts COVID, Non-COVID, or bacterial pneumonia.

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