ROLE OF DEEP LEARNING STRATEGIES IN DETECTING COVID-19 PNEUMONIA

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1. Introduction

Coronavirus (COVID-19) pandemic has killed over 5.6 million and infected 370 million people across the world. This disease was reported to originate from Wuhan city in China in December 2019. Experts have identified Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) as the causative organism [1]. In March 2020, the World Health Organization (WHO) pronounced the disease as a pandemic [2]. The back-to-back emergence of new variants such as delta and omicron variants has burdened medical care systems around the world [3, 4]. Nations across the globe are struggling to slow the spread of infection by testing and treating patients in the earliest phases by isolating people posing a high risk of transmissibility because of being in close contact with patients with confirmed infection [5]. Coronavirus is known to cause serious respiratory disease including multiple organ failures.

This rapid spread of the viral disease has created a shortage of medical healthcare infrastructure and facilities worldwide. Governments are scrambling to find key resources such as medicines, oxygen cylinders, and qualified medical practitioners to tackle pandemics. Early diagnosis and symptom-based treatment are essential for saving the lives of patients to COVID-19 [6]. Reverse transcription-polymerase chain reaction (RT-PCR) is the key testing methodology for COVID-19 diagnosis. Rapid RT-PCR testing is challenging, as it includes high false-negative rates, delays in processing, variability in test strategies, and sensitivity as low as 60-70%. Thus requiring strict testing environments restricting the quick and precise testing of suspended subjects [7]. Apart from RT-PCR testing, computed tomography (CT) and X-ray have also shown effectiveness in the diagnosis as well as evaluation of COVID-19 evolution [8,9]. Generally, the CXR modality is the first choice for radiologists to detect chest pathology and has been applied to identify or confirm COVID-19 in a small number of patients [10]. Sample chest X-Ray images for a) normal, b) COVID-19, c) SARS, and d) pneumocystis adopted from Shankar et al, 2021 have been shown in figure 1 to exemplify the pathological features [11]. It has been seen that X-ray images have a limitation to distinguish between soft tissue with a poor contrast to limit the exposure dose to the patients [12, 13]. Whereas, the CT test gives insight into pathophysiology that could reveal insights in various stages of disease detection and evolution [14]. The difference in interpretation of CT scans by different radiologists raises issues of subjectivity and errors in diagnosis [15]. CT has a high radiation dose, which makes it unsuitable for children and pregnant mothers, whereas X-rays have a low radiation dose, are widely available, and are relatively inexpensive. As a result, the X-ray is a suitable option for imaging the lungs and may be an effective technique for early identification of COVID-19, particularly in countries where laboratory kits for COVID-19 testing are prohibitively expensive [16,17,18]. However, studies have revealed that it is difficult to distinguish COVID-19 pneumonia from others caused by bacterial and fungal pathogens as their radiographic characteristics seem to be very similar [19]. Furthermore, the lungs have intricate morphological patterns that alter in size and appearance over time [20,21,22]. Based upon CT images, bacterial pneumonia is typically lobar, meaning it affects only one or more lobes. Inflammatory exudates within the intra-alveolar space cause consolidation, which affects a wide and continuous portion of the lung lobe. On the other hand, viral pneumonia is typically interstitial, appearing in CT as widespread bronchopneumonia or interstitial pneumonia involving many fissures and lobes [23]. Patchy foci of consolidation in one or more lobes of one or both lungs characterize this condition. COVID-induced pneumonia is similar to viral pneumonia, however, it mainly affects the peripheral and lower lungs. Despite these distinguishing features, many times treating physicians and radiologists can have differing views on account of training, experience, skills, and other factors.

Therefore, a technology-driven solution such as artificial intelligence (AI)-based detection framework capable of carrying out an automated, accurate, and rapid COVID-19 pneumonia screening is needed [24]. AI can assist in maintaining diagnostic radiology support with increased sensitivity in real-time [25]. Artificial intelligence (AI) breakthroughs have resulted in a significant increase in the creation of computer-aided diagnostic (CAD) systems [26-45]. Machine learning (ML) and deep learning (DL) techniques have become important disciplines to mine, analyze, and recognize patterns from data [12]. Now, AI techniques have been applied to

various medical domains; for example, pulmonary diseases [46, 47], cardiology [48, 49], and brain surgery [50, 51]. In Table 1 [52-60], we summarize various models built using AI. For instance, the CAD4COVID-CT tool is used to quantify the pulmonary parenchyma in CT scans (Manufacturers-Thirona, Nijmegen, the Netherlands). CAD4COVID-CT is a free AI-based software suite designed to aid healthcare workers in their daily tasks during the COVID-19 pandemic. The software automatically quantifies the lobar extent of COVID-19 severity from inspiratory CT scans. The software's quantitative output comprises the volume (ml) and COVID-19 impacted area (percent) for each lobe, as well as a lobar COVID-19 severity score ranging from 0 to 5. Because the total severity score is equal to the sum of each lobar score, it spans from 0 to 25. Clinical information and reference standard data are unavailable since the software only uses CT scans. The Food and Drug Administration has approved the use of CAD4COVID-CT in the United States. It is CE 0344 certified as a Class IIa medical device (FDA) [61].

Deep learning (DL) is the process of autonomously discovering the representations required for detection or classification from raw data [62]. DL has been demonstrated to be an accurate technique by extracting features from the informational dataset in hand [13]. In figure 2, we provide a flowchart of the generalized workflow for DL-based Covid-19 detection [11]. Our research group has long-standing experience in implementing AI techniques in vaccine discovery [62], network biology [63], genomics [64, 65], drug repurposing [66], and as well in computer-aided diagnosis.

In this chapter, we will describe the various deep learning strategies used in detecting COVID-19 pneumonia.

2. <u>State- of- the art literature:</u>

Following the discovery of the novel COVID-19 pandemic, several studies based on artificial intelligence (AI) techniques to detect COVID-19 from digital CXR or CT have been proposed.[67] The earliest known studies carried out using computer-aided diagnosis (CAD) have all proposed deep learning strategies for COVID-19 pneumonia diagnosis [68-72]. Some elements shared by all of these initially proposed approaches included: i) performing standard pre-processing of CT or X-Ray for using them as input dataset such as lung segmentation using U-Net [73] or similar models [68], ii) Using state-of-the-art deep neural network methods, the deep learning model is trained to the final diagnosis. We summarize important studies in Table 2 [7,4,24,74-99]. This contains information about studies carried out during the years 2020-present describing the source datasets for training and prediction models for COVID-19 pneumonia detection. In Table 3, we report other important features of the studies [7,4,24,74-99].

Several models have been proposed for image classification and computer vision applications since the ImageNet competition (ILSVRC) 2012 [20]. Based on their designs, these established models can be divided into various model families, such as AlexNet, VGG Nets, Inception Nets, ResNets, MobileNets, DenseNets, and NASNets [21], [22]. These sets of model families have evolved through time to produce different versions [21], and they have been widely adopted by other researchers to develop modified and hybrid models [44]. Recent studies have proposed new layers and filters to increase the performance of basic models, such as the Sparse Shift Filter [69], Asymmetric Convolution Block [71], Adder Networks [72], Virtual Pooling [73], Discrete Wavelet Transform [74], and HetConv [44], among others. Recently, new models based on the base models including Res2Net [100] and Wide ResNet [23] have been brought forward. Next, Log Dense Net [101] and Sparse Net [102], which use the DenseNet model are also put forward by the computer vision community. In hybrid space, the noteworthy examples includes AOGNet

[10], PNASNet [103], AmoebaNet [104], DPN [105], HCGNet [44], GCNet [106], ThiNet [107], and SKNet [108]. In most cases, CXR images are used for training input datasets rather than CT images because X-ray machines are frequently available in most hospitals and are cheaper than CT scan machines. Also, X-rays have lower ionizing radiation than CT scans [108, 109]. In the next section, we shall provide brief descriptions of some of the studies.

One of the earliest studies by Oh et al., established a patch-based deep learning strategy with segmentation and classification phases to distinguish the COVID-19 from Chest X-ray (CXR) images achieving an F1-score of 84.40% and total accuracy of 88.90% [75]. Ozturk et al. [102] introduced a DarkCovidNet DL model that used whole CXR images to recognize COVID-19. Their model was developed for a binary task classification (Normal vs. COVID-19) and a multi-class task classification- utilizing 17 convolutional layers (Pneumonia vs. Normal vs. COVID-19). DL model obtained overall diagnostic accuracies of 98.08% and 87.02%, for binary and multi-class classification tasks respectively. Wang et al. introduced a DL COVID-Net which uses CXR images to categorize COVID-19 against normal and pneumonia lung illnesses [10]. Their proposed model beat ResNet-50 and VGG-16, with positive predictive values (PPVs) of 98.9%, 90.50%, and 91.30% for COVID-19, normal, and pneumonia patients, respectively. Ardakani et al. published a study that used ten different well-established DL models to diagnose COVID-19 in ordinary clinical practice using CT images [103]. They used ResNet101 and Xception DL networks to diagnose COVID-19 against Non-COVID-19 in a binary classification job to achieve the best results with an overall accuracy of 99.40% for each.

Apostolopoulos et al. employed five well-known deep learning networks to detect the COVID-19 lesions from CXR images [37]. All of these DL models were put to the test for binary (COVID-19 vs. normal) and multiclass recognition tasks (i.e., pneumonia, COVID-19, and normal). They found that for binary and multi-class recognition tasks, VGG-19 achieved the highest overall diagnostic accuracies of 93.48 % and 98.75 %, respectively. For automatic diagnosis of COVID-19 disease, Ucar et al [105] used the Squeeze Net model, in which the hyperparameters are optimized by a Bayesian algorithm. For 3-class categorization, the proposed model had an accuracy of 98.26%. Aras et al [106] used a hybrid approach that included fine-tuning, deep feature extraction, and end-to-end training methods. For binary classification of COVID-19 and normal classes, the authors achieved a success rate of 0.92. Pathak et al [107] used the ResNet model for binary classification to extract deep features. In addition, the authors exploited cost-sensitive characteristics to improve classification accuracy. With this strategy, the best accuracy was 93.01 percent. Gour et al [108] used a pre-trained VGG19 model and a new model with 30 layers to extract deep features. A logistic regression approach was used to classify the data. Butt et al

[109] used pre-processing variables from the Hounsfield scale (HU) and a 3D CNN model for deep feature extraction. Mangal et al [110] proposed a ChexNet model of 121 layers, including convolutional and dense layers. The 3-class classification with COVID-19, normal, and pneumonia class labels had the best accuracy of 90.5 percent. Togacar et al [104] used pre-trained models from MobileNetV2 and SqueezeNet to detect COVID-19 automatically. These models were used to create a stack feature set. The SVM method produced the best classification result. To categorize COVID-19, pneumonia, and normal classes, Nour et al [44] suggested an end-to-end learning model with 5 convolutional layers. Turkoglu [90] suggested a transfer learning strategy for extracting deep features from CXR pictures using a pre-trained AlexNet model. Deep features were created by combining each layer's third dimension contributions in the trained model. For 3-class classification, the SVM classifier had a 99.18 percent accuracy. Popularly used model techniques along with their result metrics have been reported in Table 4 [7, 4, 24, 74-99].

However, using the whole CXR picture presents a set of challenges in front of the deep learning community. This is because the whole CXR image contains irrelevant or mixed textural structure data. Knowledge extraction using the entire CXR image may not be a good idea for improving any CAD system's performance. To circumvent these issues, extracting specific regions or patches from whole CXR images containing only important pathology (i.e., COVID-19 or another disease) could be a better strategy to improve performance. Thus, Regional ROI based on a DL CAD system was presented by Al-Antari and his colleagues. The proposed CAD framework for detecting and recognizing COVID-19 in the fight against pneumonia and other several lung-associated disorders [100].

3. Model Architectures

3.1 Model 1: Convolutional Neural Network

Convolutional neural networks (CNNs) have gained a lot of attraction in the current era of deep learning-based algorithms, both in general and in medical image-based applications [111]. CNN’s are preferred for image processing because they extract a lot of information from the data and are robust context learners [106]. These networks may also be taught to identify regular and diseased patterns in provided radiographic scans (i.e., X-ray and CT-scan pictures) within a second in the case of COVID19 screening. However, to train a CNN model, a substantial amount of training data is necessary, which can be regarded as a major constraint in deep learning approaches. Convolutional layers, which includes filters of various sizes, make up the majority of a CNN model's layout. Using the training dataset, the initial stage involves training to learn the trainable filters. Following the training process, the trained model can investigate the given testing samples and, as a result, accurately predict the outcome.

Using CNNs in COVID 19, Qaid et al used four convolutional layers and four dense layers. There were three convolutional layers: one with 16 filters, another one with 32 filters, and the last one with 64 filters. All of the filters were 3×3 in size, and all of the convolutional layers had a maximum pooling of 2×2. Three hidden layers of 128, 64, and 10 neurons, as well as one output layer, made up the four dense layers. The layered structure of the deep convolutional neural network is shown in Figure 3.

Apart from CNN, Qaid et al utilized several other deep learning models that have been built and tested such as TL with VGG16 and VGG19, and ML approaches. To increase accuracy, optimized hyperparameters for the proposed models were identified and deployed to extract deep features for binary and multiclass classifiers. To ensure that models were accurate in discriminating COVID-19 from other viral pneumonia diseases with numerous shared

radiographic and ambiguous signs, they tested them on a data set with three classes. The proposed models outperformed the baseline and produced encouraging results, particularly the hybrid models, which produced excellent results for both types of classifiers. They reported 100% accuracy for binary categorization in numerous circumstances. This demonstrates DL approaches' capacity to extract meaningful features, which makes ML researchers' job easier [50].

While designing architecture, four convolutional layers and four dense layers were used. There were convolutional layers: one with 16 filters, one with 32 filters, and two with 64 filters. All of the filters were 3×3 in size, and all of the convolutional layers had a maximum pooling of 2×2. Three hidden layers of 128, 64, and 10 neurons, as well as one output layer, made up the four dense layers. Three classification techniques were used in this model: binary classification between COVID-19 and normal cases, binary classification between COVID-19 and viral pneumonia cases, and multiclass classification between normal, viral pneumonia, and COVID-19 cases [50].

3.2 Model 2: Hybrid CNN with Machine Learning

As ML techniques require human experts for feature extraction, an alternative strategy is to utilize DL techniques for the automated extraction of features. These types of models use the CNN approach to extract features, which are then fed into one of the machine learning algorithms. The approach consists of two blocks—CNN and ML—one for feature extraction and the other for classification. In one of the studies, four supervised classification approaches were investigated (naive Bayes, support vector machine, random forest, and XGBoost) [106]. The collected features were then fed into the machine learning algorithm as inputs [106].

3.3 Model 3: Transfer Learning

Deep CNN training demands a significant amount of computing and memory resources, hence becoming time-consuming. In the absence of sufficient data, transfer learning (TL) offers an effective alternative for fine-tuning a CNN that has already been pre-trained on a huge set of labeled images from another category. This aids in accelerating convergence while reducing

computing complexity during the training process. The early layers of a CNN often learn low-level visual properties that are useful for most vision applications. On the other hand, the later layers learn high-level, application-specific features. As a result, for transfer learning, superficial fine-tuning of the last few layers is usually sufficient. A popular strategy is to replace the pre-trained CNN's last fully-connected layer with a new fully-connected layer with the same number of neurons as the new target application's number of classes. The remaining weights in the pre-trained network's remaining layers are kept. This relates to using the characteristics generated in the previous layer to train a linear classifier. In situations when the COVID-19 acquired dataset is found inadequate consisting of limited annotated data for training CNN from scratch, TL is accustomed to knowledge (features, weights, etc.) acquired from the source domain (DS) and source task (TS) to train newer models for the target domain (DT) and target task (TT) [112]. The basic architecture for TL (Nayak et al, 2021) is displayed in Figure 4 [113].

Thus, TL focuses on storing and applying weights (optimized) while performing image classification. VGGNet, GoogleNet, ResNet, Xception, Inception-V3, and DenseNet contain TL models. To explain further, the unprocessed data is first processed before implementing different TL models. For instance, N-CLAHE can be used to normalize images and emphasize smaller details for machine learning classifiers to notice. This includes downsizing of images to make them suitable for the algorithms. For example, 224×224 pixels for the VGG16/19 system and 299×299 pixels for the InceptionV3 system.

Techniques such as data augmentation are often used after image scaling to improve the amount and variety of images presented to the classifier. These include horizontal flip, rotation, width shift, and height shift. In one of the studies involving X-rays, the authors reported that X-Ray scans are not vertically symmetrical. Thus the resulting flipped image would not resemble a genuine chest and hence no vertical flip augmentation was applied [114]. Hemdan et al introduced a new deep learning framework; namely COVIDX-Net to assist radiologists in automatically diagnosing COVID-19 in X-ray images. COVIDX-Net provided a classification accuracy of 91% [87]. Narin et al. [115] reported three distinct CNN models for COVID-19 classification from chest X-ray images: ResNet-50, Inception-ResNetV2, and InceptionV3. They found that ResNet50 had the highest classification accuracy, i.e., 98%. For extracting imaging features from infected patients, Sethy and Behera [116] used the ResNet-50 pre-trained transfer learning approach. Support vector machines (SVM) were used to classify the data using these features and their created model had a classification accuracy of 95.34%. Farooq and Hafeez [117] proposed a multi-stage fine-tuning technique for the ResNet-50 architecture, which was pre-trained and named their developed model as COVIDResNet having an accuracy of 96.23%. Asnaoui et al. [118] conducted a comparison of eight TL algorithms for COVID-19 pneumonia classification using 5856 chest X-ray pictures to train their model. The classification accuracy of MobileNet-V2 and Inception-V3 was 96%.

3.4 Other "Out-of-the-Box" Models

1) VGG16 and VGG19

VGG16 and VGG19 [47] are convolutional neural network (CNN) designs with very small convolution filters (88) and a stride of 1, designed for large-scale image recognition applications. The level of convolution/max-pooling and fully linked layers differs between the two implementations, with VGG16 having 16 layers in the base model and VGG19 having 19 layers. VGG16 was initially created to recognize large-scale images. It overcame issues of training time and paucity of datasets by using the ImageNet data set. VGG16 has outperformed other techniques in a study conducted by Hussain et al. [81]. Their VGG16 design included 13 convolutional layers, three dense layers, and all of the convolutional layers' parameters were retained, while the dense layers were lowered to just two. The data set was used to train the weights of the dense layers. VGG16's convolutional layers were broken down into five phases: two layers with 64 filters, two layers with 128 filters, three layers with 256 filters, and three layers with 512 filters. Each convolutional phase followed maximum pooling of 2×2 and all filters were of size 3×3. One hidden layer with 128 neurons and one output layer made up the two dense layers. The network of VGG16 comprises almost 138 million parameters.

The VGG19 classifier with transfer learning is a quick and easy-to-implement machine learning model for several imaging modes that produce good results and could lead to clinically relevant diagnostic tools. VGG19 is a 19-layer model that adds one more layer to each of VGG16's final three convolutional phases [106]. M. J. Horry et al. fine-tuned the VGG19 model for each image node and each experiment to get the best results for the datasets obtained. They experimented with learning rates ranging from 103 to 106 in order-of-magnitude increments. Batch sizes ranging from 2 to 16 were used, with a hidden layer containing between 4 and 96 nodes. Dropout rates of 0.1 and 0.2 were used during the training[114].

2) ResNet50 V2

The ResNet [48] CNN was created to avoid vanishing gradient problems inherited in deep neural networks using the arrangement of skip connections between layers known as residual learning. This architecture builds a network that is easier to train, allowing for the creation of deeper networks that improve model accuracy. ResNet50 is a network with 50 layers of residual learning implementation. Even though ResNet is deeper than VGGNet, the model size of ResNet is significantly reduced due to the use of global average pooling rather than fully connected layers [119]. Resnet50 architecture has been utilized as the premise in the development of hybrid models, as it provides high performance in analysis of biomedical images [120]. It is 50 layers deep and consist of the following components:

A) Input layer: The input layer is the one to read the images first [46] and may consist of hybrid models.

B) Convolutional layer: The input image is reduced to a smaller size than the size of the filter used in the convolutional layer. In this layer, NxN size filters may be preferred. This layer's goal can be summarized as "creating feature maps" [47].

C) Activation function: For nonlinear transformation processes, activation functions are frequently used in artificial neural networks. Many activation functions have been developed, amongst which Relu, Sigmoid, and Tanh are the most popularly used [48].

D) Normalization: The output value produced by the convolution and fully connected layers is normalized in this layer [49].

E) Hidden layers/Internal layers: Several layers can be included in the architecture networks, as well as a dropout (strategy/layer) to prevent overfitting [50].

F) Pooling layer: Average and maximal pooling are the two most common pooling strategies. The network does not undertake any learning during pooling. For the pooling procedure, NxN sized filters are preferred [45].

G) SoftMax: This layer comes before the classification layer and has the same number of nodes as the output layer. It performs the probabilistic computation on the network, generating a decimal value for each class [46]. Softmax is a mathematical function that converts a vector of numbers into a vector of probabilities, where the probabilities of each value are proportional to the relative scale of each value in the vector.

H) Classification: The final layer capable of taking decisions [47].

3) <u>Inception V3</u>

The goal of CNN is to maximize the use of computing resources within the network by expanding the network's depth and width while keeping computation operations constant. The term "inception modules" was coined by the network's designers to represent an efficient network topology with skipped connections that may be utilized as a building block. To reduce dimensionality to a workable level for computation, this inception module is repeated spatially by stacking with occasional max-pooling layers [49].

4) Xception

The Xception CNN created by Google Inc. is an "extreme" version of the Inception model. The Inception modules are replaced by depth-wise separable convolutions. On a large-scale picture classification dataset, Xception was proven to outperform Inception (comprising 350 million images of 17,000 classes) [50].

5) Inception Resnet V2

The InceptionResNetV2 CNN blends the Inception and Resnet design to attain good classification performance utilizing a ResNet architecture with a low calculation cost of the Inception architecture [51].

6) NASNetLarge

Google Brain developed NASNet (Large) CNN as a data-driven dynamic network that uses reinforcement learning to find the best network topology for the image classification problem [21].

7) DenseNet121

Shorter connections between layers are used in the DenseNet 121 CNN, allowing for more accurate and economical training on very deep networks [37].

8) FCONet

TL built FCONet uses one of four state-of-the-art pre-trained deep learning models (VGG16, ResNet-50, Inception-v3, or Xception). Ko H et al built a simple 2D deep learning framework called the fast-track COVID-19 classification network (FCONet) to identify COVID-19 pneumonia based on a single chest CT scan [109]. Chest CT scans of patients with COVID-19 pneumonia, other pneumonia, and non-pneumonia disorders were utilized to train and test FCONet. These CT scans were divided into a training set and a testing set in the ratio 8:2. When compared, the performance of FCONet with the four pre-trained models (VGG16, ResNet-50, Inception-v3, and Xception), ResNet-50 outperformed the other three pre-trained models in the testing data set (sensitivity 99.58%, specificity 100.00%, and accuracy 99.87%). The ResNet-50 model had the highest detection accuracy (96.97%) in the additional external testing data set utilizing low-quality CT images, followed by Xception, Inception-v3, and VGG16 (90.71%, 89.38%, and 87.12%, respectively).

9) Grad- Cam

Gradient-weighted Class Activation Mapping (Grad-CAM) employs the gradients of any target concept to build a coarse localization map that highlights the essential places in the image for predicting the concept. This method includes creating 'visual explanations' for decisions made by a wide range of Convolutional Neural Network (CNN)-based models, hence improving their transparency [103]. Rajaraman et al demonstrated the use of iteratively pruned deep learning model ensembles for detecting pulmonary manifestations of COVID-19 with chest X-rays.

10) uAI Intelligent Assistant Analysis System

It is a deep learning-based software for COVID-19 assessment developed by United Imaging Medical Technology Company Limited (Shanghai, China). A modified 3D convolution neural network and a combined V-Net with bottleneck structures are used in this AI program. Patients' baseline CT images are fed into a deep learning-based segmentation system, which creates infected regions throughout the lung, lung lobes, and all bronchopulmonary segments. Following segmentation, multiple metrics are computed to measure the COVID-19 infection, including total infection volumes, lung lobe infection volumes, and bronchopulmonary segment infection volumes. The Intelligent Assistant Analysis System automatically classifies lesions into GGOs, sub-solid lesions, and solid lesions [18]. To compare the distribution of CT features about age and gender, the Chi-square test is utilized. To compare the incidence of infection in different lung segments, the generalized linear mixed model is utilized. Lung segment, age, and sex were employed as fixed variables in this model, while patients were used as random effects. The odds ratios (ORs) and 95% confidence intervals (CIs) are given. In COVID-19 patients, a chest CT scan paired with subsequent analysis by the use of Intelligent Assistant Analysis System may accurately assess pneumonia. The capacity of the uAI Intelligent Assistant Analysis to swiftly and reliably locate and quantify infection zones from CT scans can help in the diagnosis of COVID-19, as well as in analyzing the disease and guiding physicians in their treatment strategies [121]. Patients with COVID-19 pneumonia
have been observed to have bilateral and multilobar involvement on CT scans, with lesions occurring more frequently in the lower lobes [122].

11) Iteratively pruned model

This model learns to evaluate medical images for typical disease appearances and locate questionable density for ROI evaluation by learning hierarchical feature representations [119]. Learning CXR modality-specific features is aided by modality-specific transfer learning using a large-scale CXR collection with diverse data distribution. When transferred and fine-tuned for a comparable CXR classification task, the acquired feature representations serve as a good weight initialization and enhance model adaptation and generalization relative to ImageNet pre-trained weights. Iterative pruning of task-specific models and selection of the best-performing pruned model enhance prediction performance on test data while also reducing the number of trainable parameters. This is because a deep model has redundant network parameters (neurons) that do not contribute to improving prediction performance. If these neurons with lower activations can be found and deleted, the model becomes faster and smaller, with comparable or better performance than unpruned models. This would make it easier to use these models on web browsers and mobile phones [120].

12) COVIDX-Net

Hemdan et al. introduced the COVIDX-Net model, which consists of seven CNN models, to diagnose COVID-19 in X-ray images using deep learning models. The COVIDX-Net incorporates seven different deep convolutional neural network designs, including the updated Visual Geometry Group Network (VGG19) and Google MobileNet's second edition. Each deep neural network model can categorize the patient's status as either a negative or positive COVID-19 case by analyzing the normalized intensities of the X-ray image. COVIDX-Net has been successfully tested and evaluated using X-ray pictures. The dataset was divided into the ratio of 8:2 for the training (80 %) and testing (20 %) (Hemdan et al [87]). The VGG19 and Dense Convolutional Network (DenseNet) models perform well in automated COVID-19 classification, with F1-scores of 0.89 and 0.91 for normal and COVID-19, respectively. A new target function based on the dice overlap coefficient between the expected segmentation and the ground truth annotation is optimized during training. Their dice loss layer does not require sample re-weighting and is ideal for binary segmentation applications where the amount of background and foreground pixels are significantly unbalanced. The Dice overlap and Hausdorff distance between the anticipated demarcation and the ground truth annotation, as well as the obtained challenge score, were used to evaluate the performance [76].

13). COVID-DA: Deep Domain Adaptation from Typical Pneumonia to COVID-19

While employing deep learning for the detection of pneumonia, there are two major obstacles to overcome: 1) the disparity in data distributions between domains; 2) the difference between normal pneumonia diagnosis and COVID-19 diagnosis. To solve these issues, COVID-DA was developed. COVID-DA is a new deep domain approach for COVID-19 diagnosis. Specifically, the feature which is of adversarial adaptation to address the domain discrepancy and a novel classifier separation strategy to address the task difference. COVID-DA is proposed to effectively diagnose COVID-19 with a minimal number of COVID-19 annotations. Extensive tests have shown the efficacy and potential of COVID-DA in real-world applications [122].

14) COVID_MTNet: COVID-19 Detection with Multi-Task Deep Learning Approaches

For COVID-19 detection, COVID MTnet utilizes Inception Residual Recurrent Convolutional Neural Network with Transfer Learning (TL) technique, as well as a NABLA-N network model for segmenting COVID-19-infected regions. The detection model has an X-ray image testing accuracy of 84.67% and a CT image testing accuracy of 98.78%. It is a novel quantitative analysis technique for determining the percentage of infected regions in X-ray and CT images. The qualitative and quantitative results show that COVID-19 detection and contaminated region localization are possible [7].

4. Conclusion and Discussions

X-Ray and CT Images have been used extensively for the training of deep learning models in COVID 19 cases (Table 1 and Table 2). We observed that X-Ray images are preferred over CT images. Computer-assisted detection and diagnosis of pulmonary diseases using X-Ray images has been studied since the 1960s and has progressed with publications revealing the remarkably accurate diagnoses of a variety of disorders such as osteoporosis, breast cancer, and heart ailments. Several researchers used CNNs with transfer learning to detect lung nodules and got remarkably accurate results. Although weak contrast in X-Ray images makes it difficult to differentiate soft tissue, several researchers have included contrast enhancement as a pre-processing step in X-Ray based diagnosis. Furthermore, lung segmentation in X-Ray pictures has been a key step observed in the diagnosis of COVID-19 pneumonia, and several segmentation algorithms based on linear filtering/thresholding, rolling ball filters, and more recently CNNs have been proposed in the literature. Even though CT scans have a far higher contrast/resolution than X-Rays, issues such as low dosage and inappropriate image enhancement can result in poor image quality. The contrast of CT scans can be improved using histogram equalization techniques, particularly adaptive histogram equalization, according to several researchers. Histogram normalization, gamma correction, and contrast constrained adaptive histogram equalization have all been found to improve the quality of weak contrast CT pictures objectively.

In terms of limitations, it is difficult to automate COVID-19 screening and/or diagnosis of CXR. This is due to the inability of DL algorithms to report which features are being detected that are clinically irrelevant to COVID-19. There is a lot to be done for systematic testing of DL algorithms. Further, it is important to have clear protocols for the normalization of data coming from different sources, which are key to distinguishing correlations associated with a particular data source as opposed to the clinical usefulness of CXR image classification for respiratory illnesses.

In this chapter, we have presented several deep neural network techniques involved in the study and detection of COVID-19 pneumonia. Majority of these techniques include CNN and TL approaches. However, if the source and target domains are quite different, such as natural and medical images, TL has a very limited role to play because the networks may acquire very different high-level features in the two scenarios. The ResNet and Xception models are also frequently used models in medical imaging. Standard metrics such as accuracy, f-measure, sensitivity, specificity, and kappa statistics are the widely used parameters for reporting the performance of methods .

5. References

1. Zhu, Na, et al. "A novel coronavirus from patients with pneumonia in China, 2019." New England journal of medicine (2020).
2. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports.
3. Al-Waisy, A. S., et al. "COVID-DeepNet: hybrid multimodal deep learning system for improving COVID-19 pneumonia detection in chest X-ray images." *Computers, Materials and Continua* 67.2 (2021): 2409-2429.
4. El Asnaoui, Khalid, and Youness Chawki. "Using X-ray images and deep learning for automated detection of coronavirus disease." *Journal of Biomolecular Structure and Dynamics* (2020): 1-12..
5. Bhatraju, Pavan K., et al. "Covid-19 in critically ill patients in the Seattle region—case series." *New England Journal of Medicine* 382.21 (2020): 2012-2022.
6. Zhou, Yang, et al. "Case report on early diagnosis of COVID-19." *Disaster medicine and public health preparedness* 14.6 (2020): e22-e25.
7. Owais, Muhammad, et al. "Light-weighted ensemble network with multilevel activation visualization for robust diagnosis of COVID19 pneumonia from large-scale chest radiographic database." Applied soft computing 108 (2021): 107490.
8. Ai, Tao, et al. "Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: a report of 1014 cases." Radiology 296.2 (2020): E32-E40. 9. Fang, Yicheng, et al. "Sensitivity of chest CT for COVID-19: comparison to RT-PCR." Radiology 296.2 (2020): E115-E117
9. Hemdan, Ezz El-Din, Marwa A. Shouman, and Mohamed Esmail Karar. "Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images." *arXiv preprint arXiv:2003.11055* (2020)..
10. Shankar, K., and Eswaran Perumal. "A novel hand-crafted with deep learning features based fusion model for COVID-19 diagnosis and classification using chest X-ray images." *Complex & Intelligent Systems* 7.3 (2021): 1277-1293.
11. . Deng, Li, and Dong Yu. "Deep learning: methods and applications." *Foundations and trends in*

signal processing 7.3–4 (2014): 197-387.

12. Bengio, Yoshua, and Yann LeCun. "Scaling learning algorithms towards AI." *Large-scale kernel machines* 34.5 (2007): 1-41.
13. Harmon, S.A., Sanford, T.H., Xu, S. et al. Artificial intelligence for the detection of COVID-19 pneumonia on chest CT using multinational datasets. Nat Commun 11, 4080 (2020). https://doi.org/10.1038/s41467-020-17971-2
14. Eng, John, and David A. Bluemke. "Imaging publications in the COVID-19 pandemic: applying new research results to clinical practice." *Radiology* 297.1 (2020): E228-E231.
15. Chakraborty, Rohan, and Suhel Parvez. "COVID-19: An overview of the current pharmacological interventions, vaccines, and clinical trials." *Biochemical pharmacology* (2020): 114184.
16. Ozturk, Tulin, et al. "Automated detection of COVID-19 cases using deep neural networks with X-ray images." *Computers in biology and medicine* 121 (2020): 103792.
17. Sekeroglu, Boran, and Ilker Ozsahin. "<? covid19?> Detection of COVID-19 from Chest X-Ray Images Using Convolutional Neural Networks." *SLAS TECHNOLOGY: Translating Life Sciences Innovation* 25.6 (2020): 553-565.
18. Kermany, Daniel S., et al. "Identifying medical diagnoses and treatable diseases by image-based deep learning." *Cell* 172.5 (2018): 1122-1131..
19. Prahs, P., et al. "Deep learning to support therapy decisions for intravitreal injections." *Der Ophthalmologe: Zeitschrift der Deutschen Ophthalmologischen Gesellschaft* 115.9 (2018): 722-727.
20. Koo, Hyun Jung, et al. "Radiographic and CT features of viral pneumonia." *Radiographics* 38.3 (2018): 719-739.
21. Qin, Xu, and Zhilin Wang. "Nasnet: A neuron attention stage-by-stage net for single image deraining." *arXiv preprint arXiv:1912.03151* (2019).
22. Koo, Hyun Jung, et al. "Radiographic and CT features of viral pneumonia." *Radiographics* 38.3 (2018): 719-739..
23. Gozes, Ophir, et al. "Rapid ai development cycle for the coronavirus (covid-19) pandemic: Initial results for automated detection & patient monitoring using deep learning ct image analysis." *arXiv preprint arXiv:2003.05037* (2020)..
24. Baltazar, Lei Rigi, et al. "Artificial intelligence on COVID-19 pneumonia detection using chest xray images." Plos one 16.10 (2021): e0257884.
25. Li, Dasheng, et al. "False-negative results of real-time reverse-transcriptase polymerase chain reaction for severe acute respiratory syndrome coronavirus 2: role of deep-learning-based CT diagnosis and insights from two cases." *Korean journal of radiology* 21.4 (2020): 505-508.
26. Ghoshal, Biraja, and Allan Tucker. "Estimating uncertainty and interpretability in deep learning

for coronavirus (COVID-19) detection." *arXiv preprint arXiv:2003.10769* (2020).

27. Oh, Yujin, Sangjoon Park, and Jong Chul Ye. "Deep learning covid-19 features on cxr using limited training data sets." *IEEE transactions on medical imaging* 39.8 (2020): 2688-2700.
28. Das, Dipayan, K. C. Santosh, and Umapada Pal. "Truncated inception net: COVID-19 outbreak screening using chest X-rays." *Physical and engineering sciences in medicine* 43.3 (2020): 915-925.
29. Pereira, Rodolfo M., et al. "COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios." *Computer Methods and Programs in Biomedicine* 194 (2020): 105532.
30. Khan, Asif Iqbal, Junaid Latief Shah, and Mohammad Mudasir Bhat. "CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images." *Computer Methods and Programs in Biomedicine* 196 (2020): 105581.
31. Brunese, Luca, et al. "Explainable deep learning for pulmonary disease and coronavirus COVID-19 detection from X-rays." *Computer Methods and Programs in Biomedicine* 196 (2020): 105608.
32. Han, Zhongyi, et al. "Accurate screening of COVID-19 using attention-based deep 3D multiple instance learning." *IEEE transactions on medical imaging* 39.8 (2020): 2584-2594.
33. Mahmud, Tanvir, Md Awsafur Rahman, and Shaikh Anowarul Fattah. "CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization." *Computers in biology and medicine* 122 (2020): 103869.
34. Minaee, Shervin, et al. "Deep-covid: Predicting covid-19 from chest x-ray images using deep transfer learning." *Medical image analysis* 65 (2020): 101794.
35. Khan, Irfan Ullah, and Nida Aslam. "A deep-learning-based framework for automated diagnosis of COVID-19 using X-ray images." *Information* 11.9 (2020): 419.
36. Apostolopoulos, Ioannis D., and Tzani A. Mpesiana. "Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks." *Physical and Engineering Sciences in Medicine* 43.2 (2020): 635-640.
37. Jaiswal A., Gianchandani N., Singh D., Kumar V., Kaur M. Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning J. Biomol. Struct. Dyn., 1 (2020), pp. 1-8
38. Ardakani, Ali Abbasian, et al. "Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks." *Computers in biology and medicine* 121 (2020): 103795.,
39. Tsiknakis, Nikos, et al. "Interpretable artificial intelligence framework for COVID‑19 screening

on chest X-rays." *Experimental and Therapeutic Medicine* 20.2 (2020): 727-735.

40. Hu, Runwen, et al. "Automated diagnosis of covid-19 using deep learning and data augmentation on chest ct." *medRxiv* (2020).
41. Martínez, Fredy, Fernando Martínez, and Edwar Jacinto. "Performance evaluation of the NASNet convolutional network in the automatic identification of COVID-19." *International Journal on Advanced Science, Engineering and Information Technology* 10.2 (2020): 662.

42.

43. Nour, Majid, Zafer Cömert, and Kemal Polat. "A novel medical diagnosis model for COVID-19 infection detection based on deep features and Bayesian optimization." *Applied Soft Computing* 97 (2020): 106580.
44. Hernandez-Matamoros, Andres, et al. "Forecasting of COVID19 per regions using ARIMA models and polynomial functions." *Applied soft computing* 96 (2020): 106610.
45. Blei, David M., Andrew Y. Ng, and Michael I. Jordan. "Latent dirichlet allocation." *the Journal of machine Learning research* 3 (2003): 993-1022.
46. Saber, Shehab El-Din, and Ahmed Abdel Rahman Hashem. "Efficacy of different final irrigation activation techniques on smear layer removal." *Journal of endodontics* 37.9 (2011): 1272-1275.
47. Li, Yanghao, et al. "Adaptive batch normalization for practical domain adaptation." *Pattern Recognition* 80 (2018): 109-117.
48. Hawkins, Douglas M. "The problem of overfitting." *Journal of chemical information and computer sciences* 44.1 (2004): 1-12.
49. Yildirim, Muhammed, and Ahmet Cevahir Cinar. "A Deep Learning Based Hybrid Approach for COVID-19 Disease Detections." *Traitement du Signal* 37.3 (2020): 461-468.
50. Dias, Camila, et al. "Simulating the behaviour of choquet-like (pre) aggregation functions for image resizing in the pooling layer of deep learning networks." *International Fuzzy Systems Association World Congress*. Springer, Cham, 2019.
51. Du, Yi, et al. "Dose-area-product (DAP) modelling of Siemens Max-series X-ray digital radiography (DR) systems." *Radiation Physics and Chemistry* 181 (2021): 109311.
52. Armitage, Hanae. "Artificial intelligence rivals radiologists in screening X-rays for certain diseases." (2018).
53. Adams, Scott J., et al. "Artificial intelligence solutions for analysis of X-ray images." *Canadian Association of Radiologists Journal* 72.1 (2021): 60-72.
54. Massat, Mary Beth, and McKenna Bryant. "Thinking inside the box with AI and ML: A new kind of" insider intelligence"." *Applied Radiology* 48.1 (2019): 34-37.
55. Yassine, Hadi M., and Zubair Shah. "How could artificial intelligence aid in the fight against coronavirus? An interview with Dr Hadi M Yassine and Dr Zubair Shah by Felicity Poole,

Commissioning Editor." *Expert review of anti-infective therapy* 18.6 (2020): 493-497.

56. Dave Steiner, "Developing Deep Learning Models for Chest X-rays with Adjudicated Image Labels", *MD Research Scientist and Shravya Shetty Technical Lead Google Health*
57. Int Wound, J. "1| DELFT IMAGING AND THIRONA."
58. Gada, Utsav, et al. "X-ray Machines integration with AI." *2020 IEEE 20th International Symposium on Computational Intelligence and Informatics (CINTI)*. IEEE, 2020.
59. Vo, Luan Nguyen Quang, et al. "Early evaluation of an ultra-portable x-ray system for tuberculosis active case finding." *Tropical medicine and infectious disease* 6.3 (2021): 163
60. Kardos, Anna Sára, et al. "The diagnostic performance of deep-learning-based CT severity score to identify COVID-19 pneumonia." *The British Journal of Radiology* 95.1129 (2022): 20210759.
61. He, Kaiming, et al. "Proceedings of the IEEE conference on computer vision and pattern recognition." (2016): 770-778.
62. Rawal, Kamal, et al. "Identification of vaccine targets in pathogens and design of a vaccine using computational approaches." *Scientific reports* 11.1 (2021): 1-25.
63. Jagannadham, Jaisri, et al. "Comprehensive map of molecules implicated in obesity." *PLoS One* 11.2 (2016): e0146759.
64. Mandal, Prabhat K., et al. "Identification of insertion hot spots for non-LTR retrotransposons: computational and biochemical application to Entamoeba histolytica." *Nucleic acids research* 34.20 (2006): 5752-5763.
65. Rawal, Kamal, and Ram Ramaswamy. "Genome-wide analysis of mobile genetic element insertion sites." *Nucleic acids research* 39.16 (2011): 6864-6878.
66. Rawal, Kamal, et al. "COV-Drug Target interaction server for Covid-19 Drug Repurposing." (2021).
67. Tartaglione, Enzo, et al. "Unveiling covid-19 from chest x-ray with deep learning: a hurdles race with small data." *International Journal of Environmental Research and Public Health* 17.18 (2020): 6933.
68. Sethy, Prabira Kumar, and Santi Kumari Behera. "Detection of coronavirus disease (covid-19) based on deep features." (2020).
69. Apostolopoulos, Ioannis D., and Tzani A. Mpesiana. "Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks." *Physical and Engineering Sciences in Medicine* 43.2 (2020): 635-640.
70. Narin, Ali, Ceren Kaya, and Ziynet Pamuk. "Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks." *Pattern Analysis and Applications* (2021): 1-14.
71. Wang, Linda, Zhong Qiu Lin, and Alexander Wong. "Covid-net: A tailored deep convolutional

neural network design for detection of covid-19 cases from chest x-ray images." *Scientific Reports* 10.1 (2020): 1-12.

72. Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.
73. Ghoshal, Biraja, and Allan Tucker. "Estimating uncertainty and interpretability in deep learning for coronavirus (COVID-19) detection." *arXiv preprint arXiv:2003.10769* (2020).
74. Oh, Yujin, Sangjoon Park, and Jong Chul Ye. "Deep learning covid-19 features on cxr using limited training data sets." *IEEE transactions on medical imaging* 39.8 (2020): 2688-2700.
75. Duran-Lopez, Lourdes, et al. "COVID-XNet: A custom deep learning system to diagnose and locate COVID-19 in chest X-ray images." *Applied Sciences* 10.16 (2020): 5683.
76. Khan, Asif Iqbal, Junaid Latief Shah, and Mohammad Mudasir Bhat. "CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images." *Computer Methods and Programs in Biomedicine* 196 (2020): 105581.
77. Haque, Khandaker Foysal, and Ahmed Abdelgawad. "A deep learning approach to detect COVID-19 patients from chest X-ray images." *AI* 1.3 (2020): 418-435.
78. Sitaula, Chiranjibi, and Mohammad Belayet Hossain. "Attention-based VGG-16 model for COVID-19 chest X-ray image classification." *Applied Intelligence* 51.5 (2021): 2850-2863.
79. Xu, Xiaowei, et al. "A deep learning system to screen novel coronavirus disease 2019 pneumonia." *Engineering* 6.10 (2020): 1122-1129.
80. Hammoudi, Karim, et al. "Deep learning on chest x-ray images to detect and evaluate pneumonia cases at the era of covid-19." *Journal of Medical Systems* 45.7 (2021): 1-10.
81. Amyar, Amine, et al. "Multi-task deep learning based CT imaging analysis for COVID-19 pneumonia: Classification and segmentation." *Computers in Biology and Medicine* 126 (2020): 104037.
82. Maghdid, Halgurd S., et al. "Diagnosing COVID-19 pneumonia from X-ray and CT images using deep learning and transfer learning algorithms." *Multimodal Image Exploitation and Learning 2021*. Vol. 11734. International Society for Optics and Photonics, 2021.
83. Jain, Govardhan, et al. "A deep learning approach to detect Covid-19 coronavirus with X-ray images." *Biocybernetics and biomedical engineering* 40.4 (2020): 1391-1405.
84. Al-Waisy, A. S., et al. "COVID-DeepNet: hybrid multimodal deep learning system for improving COVID-19 pneumonia detection in chest X-ray images." *Computers, Materials and Continua* 67.2 (2021): 2409-2429.
85. Turkoglu, M. "COVID-19 detection system using chest CT images and multiple kernels-extreme learning machine based on deep neural network." *IRBM* (2021).

86. Li, Lin, et al. "Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT." *Radiology* (2020).
87. Singh, Dilbag, Vijay Kumar, and Manjit Kaur. "Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks." *European Journal of Clinical Microbiology & Infectious Diseases* 39.7 (2020): 1379-1389.
88. Wang, Linda, Zhong Qiu Lin, and Alexander Wong. "Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images." *Scientific Reports* 10.1 (2020): 1-12.
89. Sethy, Prabira Kumar, and Santi Kumari Behera. "Detection of coronavirus disease (covid-19) based on deep features." (2020).
90. Kim, Young-Gon, et al. "Deep learning-based four-region lung segmentation in chest radiography for COVID-19 diagnosis." *Diagnostics* 12.1 (2022): 101.
91. Catal Reis, Hatice. "COVID-19 Diagnosis with Deep Learning." *Ingeniería e Investigación* 42.1 (2022).
92. Bhattacharyya, Abhijit, et al. "A deep learning based approach for automatic detection of COVID-19 cases using chest X-ray images." *Biomedical Signal Processing and Control* 71 (2022): 103182.
93. Paul, Ashis, et al. "Inverted bell-curve-based ensemble of deep learning models for detection of COVID-19 from chest X-rays." *Neural Computing and Applications* (2022): 1-15.
94. Al-antari, Mugahed A., et al. "A Rapid Deep Learning Computer-Aided Diagnosis to Simultaneously Detect and Classify the Novel COVID-19 Pandemic." *2020 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*. IEEE, 2021.
95. Oh, Yujin, Sangjoon Park, and Jong Chul Ye. "Deep learning covid-19 features on cxr using limited training data sets." *IEEE transactions on medical imaging* 39.8 (2020): 2688-2700.
96. Mohamadou, Youssoufa, Aminou Halidou, and Pascalin Tiam Kapen. "A review of mathematical modeling, artificial intelligence and datasets used in the study, prediction and management of COVID-19." *Applied Intelligence* 50.11 (2020): 3913-3925.
97. Jagadeesh, M. S., and P. J. A. Alphonse. "NIT_COVID-19 at WNUT-2020 Task 2: Deep Learning Model RoBERTa for Identify Informative COVID-19 English Tweets." *W-NUT@ EMNLP*. 2020.
98. Ucar, Ferhat, and Deniz Korkmaz. "COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images." *Medical hypotheses* 140 (2020): 109761.
99. Ucar, Ferhat, and Deniz Korkmaz. "COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images." *Medical hypotheses* 140 (2020): 109761.

100. Pathak, Yadunath, et al. "Deep transfer learning based classification model for COVID-19 disease." *Irbm* (2020).

101. Gour, Mahesh, and Sweta Jain. "Stacked convolutional neural network for diagnosis of covid-19 disease from x-ray images." *arXiv preprint arXiv:2006.13817* (2020).

102. Klein, Aaron, et al. "Fast bayesian optimization of machine learning hyperparameters on large datasets." *Artificial Intelligence and Statistics*. PMLR, 2017.

103. Klein, Aaron, et al. "Fast bayesian optimization of machine learning hyperparameters on large datasets." *Artificial Intelligence and Statistics*. PMLR, 2017.

104. Minaee, Shervin, et al. "Deep-covid: Predicting covid-19 from chest x-ray images using deep transfer learning." *Medical image analysis* 65 (2020): 101794.

105. Nayak, Soumya Ranjan, et al. "Application of deep learning techniques for detection of COVID-19 cases using chest X-ray images: A comprehensive study." *Biomedical Signal Processing and Control* 64 (2021): 102365.

106. Horry, Michael J., et al. "COVID-19 detection through transfer learning using multimodal imaging data." *IEEE Access* 8 (2020): 149808-149824.

107. Narin, Ali, Ceren Kaya, and Ziynet Pamuk. "Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks." *Pattern Analysis and Applications* (2021): 1-14.

108.

109. Farooq, Muhammad, and Abdul Hafeez. "Covid-resnet: A deep learning framework for screening of covid19 from radiographs." *arXiv preprint arXiv:2003.14395* (2020).

110. El Asnaoui, Khalid, Youness Chawki, and Ali Idri. "Automated methods for detection and classification pneumonia based on x-ray images using deep learning." *Artificial intelligence and blockchain for future cybersecurity applications*. Springer, Cham, 2021. 257-284.

111. Basu, Sanhita, Sushmita Mitra, and Nilanjan Saha. "Deep learning for screening covid-19 using chest x-ray images." *2020 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE, 2020.

112. Niu, Xiao-Xiao, and Ching Y. Suen. "A novel hybrid CNN–SVM classifier for recognizing handwritten digits." *Pattern Recognition* 45.4 (2012): 1318-1325.

113. Adem, Kemal, Serhat Kiliçarslan, and Onur Cömert. "Classification and diagnosis of cervical cancer with stacked autoencoder and softmax classification." *Expert Systems with Applications* 115 (2019): 557-564.

114. Zhang, Yu-Dong, et al. "Image based fruit category classification by 13-layer deep convolutional neural network and data augmentation." *Multimedia Tools and Applications* 78.3 (2019): 3613-3632.

115. Ko, Hoon, et al. "COVID-19 pneumonia diagnosis using a simple 2D deep learning framework with a single chest CT image: model development and validation." *Journal of medical Internet research* 22.6 (2020): e19569.
116. Basu, Sanhita, Sushmita Mitra, and Nilanjan Saha. "Deep learning for screening covid-19 using chest x-ray images." *2020 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE, 2020.
117. Ye, Zheng, et al. "Chest CT manifestations of new coronavirus disease 2019 (COVID-19): a pictorial review." *European radiology* 30.8 (2020): 4381-4389.
118. Rajaraman, Sivaramakrishnan, et al. "Iteratively pruned deep learning ensembles for COVID-19 detection in chest X-rays." *IEEE Access* 8 (2020): 115041-115050.
119. Rajaraman, Sivaramakrishnan, et al. "Iteratively pruned deep learning ensembles for COVID-19 detection in chest X-rays." *IEEE Access* 8 (2020): 115041-115050.
120. Litjens, Geert, et al. "Evaluation of prostate segmentation algorithms for MRI: the PROMISE12 challenge." *Medical image analysis* 18.2 (2014): 359-373
121. Zhang, Hai-tao, et al. "Automated detection and quantification of COVID-19 pneumonia: CT imaging analysis by a deep learning-based software." *European journal of nuclear medicine and molecular imaging* 47.11 (2020): 2525-2532.
122. Zhang, Yifan, et al. "COVID-DA: Deep domain adaptation from typical pneumonia to COVID-19." *arXiv preprint arXiv:2005.01577* (2020).