A review of Deep learning Techniques for COVID-19 identification on Chest CT images

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Abstract. The current COVID-19 pandemic is a serious threat to humanity that directly affects the lungs. Automatic identification of COVID-19 is a challenge for health care officials. The standard gold method for diagnosing COVID-19 is Reverse Transcription Polymerase Chain Reaction (RT-PCR) to collect swabs from affected people. Some limitations encountered while collecting swabs are related to accuracy and long-time duration. Chest CT (Computed Tomography) is another test method that helps healthcare providers quickly identify the infected lung areas. It was used as a supporting tool for identifying COVID-19 in an earlier stage. With the help of deep learning, the CT imaging characteristics of COVID-19. Researchers have proven it to be highly effective for COVID-19 CT image classification. In this study, we review the recent deep learning techniques that can use to detect the COVID-19 disease. Relevant studies were collected by various databases such as Web of Science, Google Scholar, and PubMed. Finally, we compare the results of different deep learning models, and CT image analysis is discussed.

Keywords: Artificial Intelligence · COVID-19 · CT images · Deep Learning · RT-PCR.

1 Introduction

The new strain of coronavirus (COVID-19) pandemic-SARS-CoV-2 was first reported in Wuhan, China in December 2019 and has since spread across the whole world. Currently, the total number of COVID-19 is around 19.5 million with 4 million deaths [15]. Coronaviruses are a family of viruses that can cause respiratory illness in humans. They belong to the subfamily of Corona virinae and is a part of the coronaviridae family. They are known as Corona due to crown like spike structure on the virus's outer surface under an electron microscope. Its RNA is single-stranded with 80-120nm diameter and nucleic material ranging from 26 to 32kbs in length [55]. Usually, it is divided into four types, namely alpha (α), beta (β), gamma (γ), and delta (δ), which affect animals, birds, and humans [39].

Coronaviruses usually originate from animals and are typically transferred to humans in a mutated form. The virus can spread from an infected person’s mouth or nose in small liquid particles when they cough, sneeze, speak or breathe [44]. These particles range from larger respiratory droplets to smaller aerosols. COVID-19 transmitted through air and people in close contact with each other. It was declared a global pandemic by the World Health Organization (WHO). Symptoms of the COVID-19 infection include dry cough, sore throat, fever which mainly affects the respiratory system [6]. The incubation period of COVID-19 ranges from 1 to 14 days, symptoms developing 3-7 days and, the longest incubation period can reach up to 24 days.

Early identification can reduce the transmission of COVID-19 infection. Initial Clinical testing RT-PCR conducted is well suited for early detection and collects swabs specimens from the infected patients [16]. The test is manual and time-consuming; results take 2 or 3 days. Researchers prove that sometimes false- positive results are shown while proceeding with RT-PCR testing. This test may not be helpful for the faster diagnosis of COVID-19. Speedy, accessible, reasonable, and low-cost spotting of COVID-19 is vital in slowing the transmission of COVID-19 infection. Medical experts and researchers suggest several testing methods that can be used to detect COVID-19 including using X- ray imaging [17], Ultrasound [59], and (Computed Tomography) CT [49].

The X-ray is cost-effective to define lung infections but does not show any abnormalities in the earlier stage [48]. Ultrasound images have no side effects and are used in bedside patients. Also, low costs generally do not detect lesions or abnormalities on the lungs [57]. As such, CT has been suggested, as one of the effective imaging methods. CT helps with early detection, observation, and
disease evaluation. Besides lung infection problems can be easily determined resulting into faster diagnosis of COVID-19. Clinicians analyze and predict virus disease based on the variations on CTs. Computer science researchers have developed an early detection tool for diagnosing COVID-19.

Various DL techniques have been adopted to detect, diagnose, classify, and predict COVID-19. These techniques produce the best accurate models for handling medical datasets such as prediction of brain abnormalities, bacteria classification, different types of cancer, and biomedical image segmentation. Recently, most researchers have employed Deep Learning techniques to facilitate COVID-19 identification on chest CT images. Deep learning algorithms can automatically generate the COVID-19 identification characteristics. A well-known deep learning model is CNN performing pixel-wise segmentation to use global and local features. Computer Researchers developed several deep learning architectures for automated detection of COVID-19 and provided efficient accuracy.

In this paper, we systematically review various Deep learning methods that have been used recently to detect and diagnose COVID on CT images. We surveyed over 50 papers. Among these papers, we evaluate how the COVID CT images collected from various databases also implement deep learning techniques for early identification of the COVID symptoms earlier. The remaining sections of this paper are organized as follows. Section 2 describes the methodology Section, and Section 3 defines the CT image datasets. Also, Section 4 compares various deep learning techniques for COVID identification. Finally, Section 5 discusses this paper’s conclusion by highlighting the limitations and future research directions.

2 METHODOLOGY

2.1 SEARCH STRATEGY

In this review, related journal articles are collected from valid databases. More than 90 papers are gathered, and 25 papers are filtered out. In this study, papers are selected by the keywords Artificial Intelligence, COVID-19, Convolutional Neural Network, CT-images, and Deep Learning. Our search query consists of the following keywords: [Artificial Intelligence] AND [Convolutional Neural Network] AND [COVID-19] AND [CT images] AND [Deep Learning]. After the search, filtered papers are mentioned to various deep learning techniques that are primarily applied in the medical field—these papers only direct COVID-19 disease detection by using several deep learning models.

2.2 CT IMAGES

Computer-aided methods are used to detect and diagnose the abnormalities or variations from chest CT (Computed Tomography) images. Several Deep learning studies have evolved while detecting the COVID-19 disease. CT is basically the best imaging technique for lung infections or variations, and the physician denoted it as the gold standard. While scanning the human lungs, CT produces several images, and physicians quickly analyze the variations. CT scans define the clear radiological findings of COVID-19 patients and help in a more structured and accessible manner produce results at a fast speed. COVID-19 Chest CTs have some abnormalities such as ground-glass opacities (GGO), Broncho vascular thickening in the lesion, crazy paving, and parenchymal bands are present in the lungs. These findings are kept on the COVID-19 patient’s chest CT images in Figure 1.

2.3 COVID-19 detection in CT images:

Diagnostics play an essential role in the control measures of COVID-19. Several detection tools are available to find the disease severity. Chest CT scans are the familiar fast diagnostic tool to diagnose the earlier stage of COVID-19 patients. COVID chest CT appearances are classified into four categories: 1) Typical Appearance 2) Indeterminate appearance, 3) Atypical appearance 4) Negative for Pneumonia.
Fig. 1: An example CT image of Lung showing different parts and the COVID symptoms.

**Typical Appearance:** It describes the expected behavior of the lungs such as reverse halo sign peripheral, bilateral, ground-glass opacities or without consolidation or visible intralobular lines. A central ground-glass opacities characterize the appearance of reversed halo sign is encircled by denser air–space consolidation with the shape of a crescent or a ring.

**Indeterminate appearance:** It is not determined or fixed—a few very small GGO with a non-rounded and non-peripheral distribution.

**Atypical appearance:** The presence of isolated lobar or segmental consolidation without GGO and smooth interlobular septal thickening with pleural effusion.

**Negative for Pneumonia:** There are no features to suggest pneumonia, absence of GGO, and consolidation.

3 COVID-19 DATASET

Several public databases are available on many websites like Kaggle and GitHub. They provide many Chest CT images; Deep learning models handle large volumes of data using the algorithms to extract the image and show good accuracy results. Kaggle is a large data repository containing different data set types like text, numeric, and multimedia [52]. Also, many COVID-related data set images are available grouped as classes. It supports various file formats anyone can easily access and create their own databases. The main advantage of using Kaggle is that notebook creation users can view adding code for the dataset they access as public or private.

4 DEEP LEARNING FOR COVID DETECTION

Various deep learning approaches are developed to diagnose COVID-19 quickly. Using Classification, Segmentation, and prediction tasks done with the help of deep learning models [41]. In this context, the researchers handled various deep learning methods with clinicians’ use in the detection
Deep Learning-based models have more efficacies to proceed with an accurate and efficient system for detecting and diagnosing COVID-19. Using classification models to identify the coronavirus disease patients and with the help of deep layers [1]. Segmentation describes the lungs' affected area, and manual segmentation takes more time. Prediction identifies the risk of COVID-19 infection.

Deep Learning algorithms handle large volumes of data and produce accurate results. It establishes a model for showing the coronavirus-affected person in an earlier stage. Deep Learning Technology uses CNN models to analyze how viruses affect humans [7]. The Deep Convolutional Neural Network (DCNN) can learn the imaging characteristics of COVID-19 patients. Deep Learning Architectures such as AlexNet [54], VGG16 [2], VGG19 [2], GoogLeNet [29], ResNet18 [2], ResNet50 [22], ShuffleNet [16] are the efficient networks used for early detection of COVID-19 patients using CT images. The ShuffleNet architecture for COVID detection is shown in Figure 2

**4.1 Overview of Deep Learning**

Deep Learning is a sub-domain of machine learning based on artificial neural networks. A Deep Learning algorithm uses multiple layers to extract higher-level features from the raw input progressively. It trains on large amounts of data using GPU (Graphics processing units) to speed up computational processes. GPUs have been developed and optimized specifically for deep learning. Deep Learning also refers to a class of Artificial Neural Networks (ANNs) composed of many processing layers. ANN helps interpret the features of data and their relationships in which important information is processed through multiple stages of processing the data.

**Deep Learning and the Human Brain** Deep learning works with artificial neural networks designed to imitate how humans think and learn. Deep understanding consists of artificial neural networks modeled on similar networks present in the human brain. In deep learning, we don’t need to program everything explicitly. Deep Neural Networks (DNNs) have several networks where each layer can perform complex operations such as representation and abstraction that make sense of images, sound, and text.

The human brain is the central organ of the human nervous system. The brain and the rest of the nervous system are composed of many different types of cells, but the primary functional unit is a neuron. A single neuron in the human brain receives thousands of signals from other neurons. All sensations, movements, thoughts, memories, and feelings result from signals that pass through neurons.

**4.2 Common Layers in DL model**

The layers are the blocks of Deep Learning. A layer in a deep learning model is a structure or network topology in the model’s architecture, which takes information from the previous layers and then passes information to the next layer. There are several familiar layers in deep learning: The Convolutional layer, Recurrent layer, Preprocessing layer, Normalization layer, Regularization layer, Attention layer, Reshaping layer, Merging layer, Locally connected Activation layer, and Maximum pooling layer. Some of the layers are discussed below.
Table 1: Comparison of deep learning based COVID classification models

| Model        | No. of CT images | Description | Accuracy (%) |
|--------------|------------------|-------------|--------------|
| ResNet [50]  | Total: 618 COVID: 219 Pneumonia: 224 Normal: 175 | Residual Network (ResNet) built with various layers looks like a pyramidal structure. | 86.70         |
| DenseNet121 [26] | Total:757 COVID:360 Non-COVID:397 | Accurately performs where the infected areas present in the lungs. | 84.07         |
| AlexNet [54] | Total: 7500 COVID: 2500 Lung tumour:2500 Normal: 2500 | Classify high dimensional convolutional features with less time. | 98.25         |
| EfficientNet [30] | Total: 3294 COVID: 1601 Normal: 1693 | Compound scaling method based architecture was built | 87.68         |
| DCNN [15]    | Total : 1065 COVID: 325 Pneumonia: 740 | Multiple units can be defined. Hierarchy structure of the class can be represented. | 85.20         |
| GoogLeNet [29] | Total : 746 COVID: 349 Normal: 397 | Kernel sizes and inception layers obtained in this model. Reduce the dimensional size and computational cost. | 91.72         |
| DRENet [37]  | Total:1282 COVID: 777 Pneumonia: 505 | Define the top-K information image details of the lungs and also diagnose higher level predictions. | 86.00         |
Convolutional Layer  A Convolution has a set of rules when two sources of information are interconnected. A convolutional layer contains a set of filters whose parameters need to be learned. The height and weight of the filters are smaller than those of the input volume. Each filter is convolved with the input volume to compute an activation map made of neurons. Convolutional layers apply a convolution operation to the input, passing the result to the next layer [53]. A convolution converts all the pixels in its receptive field into a single value, as shown in Figure 3.

Recurrent Layer  A group of Layers to form recurrent networks consists of several classes. It is a type of neural network with previous step outputs. You are fed as an input of the current step. It uses the same parameters for each input as it performs the same task on all the inputs or hidden layers to produce the output. It allows continuing information related to past knowledge by gaining a special kind of looped structure. Recurrent layers can be used similarly to feed-forward layers except that the input shape is expected to be (batch_size, sequence_length, num_inputs) [20]. A reverse operation is performed in the following Figure 4.
Preprocessing Layer  Preprocessing Layer takes raw images or raw structured data as input and exports the end-to-end models \cite{22}. It handles its own feature normalization or feature value indexing. Preprocessing Layer includes text, numerical, categorical, image preprocessing, and image augmentation layers. Several classes were obtained, such as text vectorization, normalization, category encoding, etc.

Normalization Layer  This layer was first introduced by Ba et al. in 2016. It normalizes the input and also speeds up stabilizes the learning process. It includes two classes, Batch normalization, and Layer normalization, as shown in Figure 5.

Batch Normalization  Batch normalization focuses on the standardized inputs to any particular layer (i.e., activations from previous layers). Standardizing the inputs means that inputs to any layer in the network should have approximately zero mean and unit variance. Batch normalization applies a transformation that maintains the mean output close to 0 and the standard deviation close to 1.

Layer Normalization  Layer normalization (LayerNorm) is a technique to normalize the distributions of intermediate layers. It enables smoother gradients, faster training, and better generalization accuracy. Layer Normalization directly estimates the normalization statistics from the summed inputs to the neurons within a hidden layer. This normalization happens across the axes.

Regularisation Layers  During optimization, this layer is used for applying penalties on layer activities. It reduces the error by fitting a function appropriately on the given training set. Regularizers allow you to apply penalties on layer parameters or layer activity during optimization. These penalties are summed into the loss function that the network optimizes. The Dropout layer randomly sets input units to 0 with a rated frequency at each step during training time, which helps prevent overfitting.

4.3 Classification Model

Early detection models have been developed for automatically identifying the COVID-19 patients. Numerous classification models are available to handle disease detection efficiently. Deep learning classification models automatically detect the COVID-19 patients using CT images \cite{1}. A well-known Deep Learning model is Convolutional Neural Network (CNN) which is a type of artificial neural network used in image recognition and processing pixel data. It has convolutional layers, pooling layers, and fully connected layers, and it is used for image processing, classification, segmentation, and other auto correlated data \cite{51}.
**CNN Architecture** CNN is the sub-class of Deep neural networks. It is used in image recognition and processing specifically designed to process pixel data. CNN is a type of neural network model which allows working with images and videos. Deep Learning has proved to be a potential tool because of its ability to handle large amounts of data. CNN takes the image’s raw pixel data, trains the model, and automatically extracts the features for better classification. Common layers occur in a convolutional neural network: the convolutional layer, the pooling layer, the ReLU correction layer, and the fully-connected layer, as shown in Figure 6.

**Convolutional Layer** The main component of CNN architecture is the convolutional layer as shown in Figure 7. Convolutional layers are the primary building blocks used in convolutional neural networks. It performs feature extraction, which produces a combination of linear and nonlinear operations.

**Pooling Layer** Another layer is the pooling layer; it is added after the convolutional layer; it reduces the size of the representation to reduce the number of parameters and computation in the
network. The vital operation of pooling is max pooling as shown in Figure 8. It extracts patches from the input feature maps and gets outputs from the maximum value in each patch; finally, it discards all the other values.

**Fully Connected Layer** Fully Connected layers in neural networks are those layers where all the inputs from one layer are connected to every activation unit of the next layer. The inputs to the fully connected layer are the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer. A fully connected layer compiles the data extracted by previous layers, such as a pooling or convolutional layer, which is flattened and then fed to form the final output, as shown in Figure 9.

Some sample classification models such as ResNet [50], DenseNet121 [20], AlexNet [51], EfficientNet [36], DCNN [15], GoogLeNet [29], DRENet [37] are defined in Table 1. These models are applied in the CT images and provide efficient accuracy.
4.4 ResNet

ResNet was designed by Kaiming in 2015 [14] that mound residual blocks on top of each other to form a network. An artificial neural network builds on constructs known from pyramidal cells in the cerebral cortex. ResNet uses residual blocks with connections that connect the input of one layer to the output of another layer, also known as shortcut connections. Residual Network (ResNet), built with various layers, looks like a pyramidal structure. An example of ResNet is shown in Figure 10. ResNet consists of three layers of three blocks containing the Convolutional layer, Batch normalization, and Relu. There is one fully connected layer at the end. In [31], the authors implemented ResNet and tested its performance on a COVID dataset. This dataset consists of 618 images (COVID: 219, Pneumonia: 224, Normal: 175). The performance of ResNet achieved an accuracy of 86.70%.

4.5 DenseNet

A DenseNet is similar to a convolutional neural network that utilises dense connections between layers; through Dense Blocks, it directly connects all layers. DenseNet and its concatenated (.) attributes combine the previous layer output with a future layer. An example of DenseNet is shown in Figure 11 which shows the four-layer dense block with the growth rate k=3. The DenseNet Architecture aims to fix this problem by densely connecting all layers. Figure 11 shows the DenseNet model which consists of four blocks: Batch normalization, ReLU, and convolutional layers. DenseNet is an easy communication model for improving information flow between layers. DenseNet has various transition blocks and dense blocks situated between two adjacent dense blocks. In [26], the authors implemented DenseNet and tested its performance on a COVID dataset. It consists of total 757 images (COVID: 360, Non-COVID: 397). Using these COVID CT images, ResNet achieved an accuracy of 84.07%.

4.6 AlexNet

The AlexNet was introduced in 2012, and Alex Krizhevsky developed it. AlexNet network performs feature selection and image category classification for input images. The AlexNet network has convolutional layers for image feature selection, and three fully connected layers for image classification [21]. It attached ReLU activations after every convolutional and fully-connected layer. An example of AlexNet is shown in Figure 12 consists of five convolutional layers followed by the max-pooling layers finally connected with three fully connected layers. In [54], the authors
implemented AlexNet and tested its performance on a COVID dataset. This dataset consists of a total of 7500 images (COVID: 2500, Lung tumor: 2500, Normal: 2500). From this dataset using this AlexNet achieved an accuracy of 98.25%.

4.7 EfficientNet

EfficientNet was developed by Mingxing Tan and Quoc V. Le in 2019. It performs the scaling method that scales all dimensions of depth/width/resolution in the same size using a compound coefficient. Efficient-Net Models are pre-trained and used for transfer learning in image classification problems. There are eight original EfficientNet models EfficientNet-B0 - EfficientNet-B7. EfficientNet network architecture and scaling method scale all depth/width/resolution dimensions using a compound coefficient. EfficientNet uses a compound coefficient to uniformly scale network width, depth, and resolution in a principled way [26]. In [36], this dataset contains 3294 CT images (COVID: 1601, Normal: 1693). EfficientNet models achieve both higher accuracy and better efficiency.

4.8 DCNN

DCNN was first introduced in the 1980s by Yann LeCun. Convolutional networks using convolutional layers. It is usually combined with the pooling layers, and the output is fed to the fully connected layers. A Convolutional neural network (CNN) is a neural network that has one or more
convolutional layers and is used mainly for image processing and classification. CNN is automatically detects the essential features without any human supervision. An example of DCNN is shown in Figure 13, it contains two convolutional layers, two pooling layers, and finally connected with a fully connected layer. In [35], the authors implemented DCNN and tested its performance on a COVID dataset. This dataset consists of 1065 images (COVID: 325, Pneumonia: 740). DCNN model can be used to detect the COVID-19 in Chest CT images and achieve an accuracy of 85.20%.

4.9 GoogLeNet

The author first proposed GoogLeNet in 2018. The Google team developed it. GoogLeNet neural network based on the Inception architecture allows the network to select between multiple convolutional filter sizes in each block. Receptive fields, various kernel sizes, inception layers are included in this model. An example of GoogLeNet is shown in Figure 14. GoogleNet consists of 4 convolutional layers, including input and output layers. The second layer is a convolutional layer of size (28x28x10) followed by a pooling layer. The following three layers (c2, c3, c4) are also convolutional layers of size, which follow a pooling layer (p2). The seventh layer is an inception layer that combines all those layers. This inception layer aims to allow the network to choose between multiple convolutional filter sizes in each block and enhance the recognition accuracy. It is followed by a pooling layer of size (80). The final layer is fully connected of size (80), followed by the output layer. In [29], the authors implemented GoogLeNet and tested its performance on a COVID dataset. This dataset consists of 746 images (COVID: 349, Normal: 397). They were using this GoogLeNet to achieve an accuracy of 91.72%.

4.10 DRENet

DRENet has been proven to detect objects in images. It extracts top-k details from each image. Residual neural networks utilized skip connections or shortcuts to jump over some layers. In [37], the authors implemented DRENet and tested its performance on a COVID dataset. This dataset consists of 1282 images (COVID: 777, Pneumonia: 505). This DRENet achieved an accuracy of 86.00%.

4.11 Segmentation based Models

Segmentation models can be used to detect the infected lung region. Mainly identify the shape of the present part. It specifies the defect inside the COVID-19 chest CT images. Some of the sample models like U-Net [10], FCN [23], VB-Net [33] are discussed in Table 2. These models
are specified accurately in the symptomatic region in the lungs. Using segmentation algorithms closed with related region merging techniques to perform specific actions. Segmentation performed in the particular areas of the lungs that predicted areas are changed into pixel predictions. Pixel can be labeled depending on the scoring system. Segmentation models handle some other diseases presented inside the lungs. These models characterize the number of CT images for the training and testing process. A fully Convolutional Network (FCN) has connected layers as sampling, pooling, and convolution. U-Net model based on decoder-encoder architecture, fast and exact segmentation of images.

Table 2: Comparison of Segmentation models for COVID identification

| Model  | No. of CT images | Description | Accuracy (%) |
|--------|------------------|-------------|--------------|
| U-net [10] | Total CT slices: | Encoding and decoding transformations performed are also recommended for medical imaging segmentation. | 94.8 |
| | 270 COVID: 120 Normal: 150 | | |
| FCN [23] | Total: | Minimize the number of parameters and less computational time to provide accuracy. | 99.00 |
| | COVID: 492 Normal: 447 | | |
| VB-Net [33] | Total: 649 | They have segmented the infected regions of the lungs in a loop method. | 91.60 |
4.12 U-Net

U-Net was created by Olaf Ronneberger et al. in 2015 [30]. It consists of contracting and expansive paths, which gives it a U-shaped architecture. A convolutional network consists of convolutions, each followed by a rectified linear unit (ReLU) and a max-pooling operation. U-Net and an equal number of pooling and sampling layers [30]. All the Convolutional layers are connected with sigmoids. It utilizes deconvolutional layer skip connections between up-sampling and down-sampling layers. It applies convolution blocks followed by a max pool downsampling to encode the input image into feature representations at multiple different levels. An example U-Net is shown in Figure 15, consisting of 9 convolutional layers connected with the sigmoid. In [10], authors implemented GoogLeNet and tested its performance on a COVID dataset. This dataset consists of 270 CT slices (COVID: 120, Normal: 150). This U-Net achieved an accuracy of 94.8%.

4.13 FCN

Fully Convolutional Networks (FCNs) are built using locally connected layers, such as convolution, pooling, and upsampling [23]. It only performs convolution operations; no dense layer is used in FCN. It also reduces the number of parameters and computation time. FCN model contains downsampling path and upsampling path. The downsampling path is responsible for capturing semantic/contextual information, and the Upsampling path is responsible for recovering spatial information. In this model, networks transform the whole convolutional models replacing FC layers, and get output as a local map. It performs the tasks only in fully connected layers. Many skip connections have been added to the network from the lower layers to the end layer. An example FCN is shown in Figure 16 describing the four convolutional layers combined with pooling layers. In [23], the authors implemented FCN and tested its performance on a COVID dataset. This dataset consists of 939 CT images (COVID: 492, Normal: 447). This FCN achieved an accuracy of 99.00%.

4.14 VB-Net:

VB-Net is a modified 3D convolutional neural network that combines V-Net with a bottle-neck structure [34]. VB-Net consists of two paths. This model segments the infected lung region based on the loop method. The Contracting path performs downsampling done convolution operations to extract the image features. The expansive path serves up-sampling to integrate fine-grained image
features [33]. The speed of VB-Net is much faster because the bottle-neck structure is incorporated in VB-Net. In [33], the authors implemented VB-Net and tested its performance on a COVID dataset. This dataset consists of a total of 649 CT. This VB-Net achieved an accuracy of 91.60%.

5 CONCLUSION AND FUTURE WORK

In this review, deep learning methods identified the severity of COVID-19 with CT images. Analyzing the infected lung area with the help of a radiologist and RT-PCR test results is an aid of the final decision. Large numbers of open source CT image databases are available. Other than COVID-19, infections inside the lungs like lesions, cancer, pneumonia, and lung-related problems are also detected while analyzing CT images using deep learning models. Abnormalities are present in the lung area researchers find out with the help of deep learning methodology. Deep learning models raised the accuracy level of classification and segmentation. Classification models automatically separate the COVID-19 CT images and other diseases. The future challenge of the review is differentiating the stages of COVID-19 and the accuracy level.

References

1. Amyar, A., Modzelewski, R., Li, H., Ruan, S.: Multi-task deep learning based ct imaging analysis for covid-19 pneumonia: Classification and segmentation. Computers in Biology and Medicine 126, 104037 (2020)
2. Ardakani, A.A., Kanafi, A.R., Acharya, U.R., Khadem, N., Mohammadi, A.: 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, 103795 (2020)
3. Ba, J.L., Kiros, J.R., Hinton, G.E.: Layer normalization. arXiv preprint arXiv:1607.06450 (2016)
4. Bernheim, A., Mei, X., Huang, M., Yang, Y., Fayad, Z.A., Zhang, N., Diao, K., Lin, B., Zhu, X., Li, K., et al.: Chest ct findings in coronavirus disease-19 (covid-19): relationship to duration of infection. Radiology (2020)
5. Buonsenso, D., Pata, D., Chiaretti, A.: Covid-19 outbreak: less stethoscope, more ultrasound. The Lancet Respiratory Medicine 8(5), e27 (2020)
6. Chen, N., Zhou, M., Dong, X., Qu, J., Gong, F., Han, Y., Qiu, Y., Wang, J., Liu, Y., Wei, Y., et al.: Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in wuhan, china: a descriptive study. The lancet 395(10223), 507–513 (2020)
7. Ciaburro, G., Venkateswaran, B.: Neural Networks with R: Smart models using CNN, RNN, deep learning, and artificial intelligence principles. Packt Publishing Ltd (2017)
8. computersciencelviki: Max-pooling / pooling (2018), https://computersciencelviki.org/index.php/Max-pooling_/Pooling, last accessed 27 February 2018
9. Fang, Y., Zhang, H., Xu, Y., Xie, J., Pang, P., Ji, W.: Ct manifestations of two cases of 2019 novel coronavirus (2019-ncov) pneumonia. Radiology (2020)
10. Gozes, O., Frid-Adar, M., Sagie, N., Zhang, H., Ji, W., Greenspan, H.: Coronavirus detection and analysis on chest ct with deep learning. arXiv preprint arXiv:2004.02640 (2020)
11. Guo, Z., Chen, Q., Wu, G., Xu, Y., Shibasaki, R., Shao, X.: Village building identification based on ensemble convolutional neural networks. Sensors 17(11), 2487 (2017)
12. Han, R., Huang, L., Jiang, H., Dong, J., Peng, H., Zhang, D., et al.: Early clinical and ct manifestations of coronavirus disease 2019 (covid-19) pneumonia. AJR Am J Roentgenol 215(2), 338–43 (2020)
13. Haque, I.R.I., Neubert, J.: Deep learning approaches to biomedical image segmentation. Informatics in Medicine Unlocked 18, 100297 (2020)
14. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 770–778 (2016)
15. 't Hoen, E.: Novel coronavirus (2019-ncov): situation report, 11 (2020). https://apps.who.int/iris/handle/10665/330776, last accessed 2020
16. Hu, R., Ruan, G., Xiang, S., Huang, M., Liang, Q., Li, J.: Automated diagnosis of covid-19 using deep learning and data augmentation on chest ct. Medrxiv (2020)
17. Ismael, A.M., Şengüür, A.: Deep learning approaches for covid-19 detection based on chest x-ray images. Expert Systems with Applications 164, 114054 (2021)
18. Ismael, S.A.A., Mohammed, A., Hefny, H.: An enhanced deep learning approach for brain cancer mri images classification using residual networks. Artificial intelligence in medicine 102, 101779 (2020)
19. Kayhan, S., Kocaçoğ, E.: Pulmonary fibrosis due to covid-19 pneumonia. Korean Journal of Radiology 21(11), 1273 (2020)
20. Khadidos, A., Khadidos, A.O., Kannan, S., Natarajan, Y., Mohanty, S.N., Tsaramirsis, G.; Analysis of covid-19 infections on a ct image using deepsense model. Frontiers in public health 8, 599550 (2020)
21. Kumar, R., Khan, A.A., Kumar, J., Gollizar, N.A., Zhang, S., Ting, Y., Zheng, C., Wang, W., et al.: Blockchain-federated-learning and deep learning models for covid-19 detection using ct imaging. IEEE Sensors Journal 21(14), 16301–16314 (2021)
22. Kvet, M., Matiasko, K.: Temporal data performance optimization using preprocessing layer. Journal of Information Systems Engineering & Management 3(2), 13 (2018)
23. Long, J., Shelhamer, E., Darrell, T.: Fully convolutional networks for semantic segmentation. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 3431–3440 (2015)
24. Maeda-Gutiérrez, V., Galvan-Tejada, C.E., Zanella-Calzada, L.A., Celaya-Padilla, J.M., Galván-Tejada, J.I., Gamboa-Rosales, H., Luna-Garcia, H., Magallanes-Quintanar, R., Guerrero Mendez, C.A., Olvera-Olvera, C.A.: Comparison of convolutional neural network architectures for classification of tomato plant diseases. Applied Sciences 10(4), 1245 (2020)
25. Marques, G., Agarwal, D., de la Torre Díez, I.: Automated medical diagnosis of covid-19 through efficientnet convolutional neural network. Applied soft computing 96, 106691 (2020)
26. Mishra, A.K., Das, S.K., Roy, P., Bandyopadhyay, S.: Identifying covid19 from chest ct images: a deep convolutional neural networks based approach. Journal of Healthcare Engineering 2020 (2020)
27. NUSANTARA, B.: Convolutional neural network. Dostupné také z: http://socs. binus. ac. id/2017/02/27/convolutional-neural-network (2017)
28. oreilly: Convolutional neural networks (2022), https://www.oreilly.com/library/view/learning-tensorflow/9781491978504/ch04.html, last accessed 2022
29. Pham, T.D.: A comprehensive study on classification of covid-19 on computed tomography with pre-trained convolutional neural networks. Scientific reports 10(1), 1–8 (2020)
30. Ronneberger, O., Fischer, P., Brox, T.: U-net: Convolutional networks for biomedical image segmentation. In: International Conference on Medical image computing and computer-assisted intervention. pp. 234–241. Springer (2015)
31. Sadiq, Z., Rana, S., Mahfoud, Z., Raoof, A.: Systematic review and meta-analysis of chest radiograph (cxr) findings in covid-19. Clinical imaging 80, 229–238 (2021)
32. Shahid, F., Zameer, A., Muneeb, M.: Predictions for covid-19 with deep learning models of lstm, gru and bi-lstm. Chaos, Solitons & Fractals 140, 110212 (2020)
33. Shan, F., Gao, Y., Wang, J., Shi, W., Shi, N., Han, M., Xue, Z., Shen, D., Shi, Y.: Lung infection quantification of covid-19 in ct images with deep learning. arXiv preprint arXiv:2003.04655 (2020)
34. Shan, F., Gao, Y., Wang, J., Shi, W., Shi, N., Han, M., Xue, Z., Shen, D., Shi, Y.: Abnormal lung quantification in chest ct images of covid-19 patients with deep learning and its application to severity prediction. Medical physics 48(4), 1633–1645 (2021)
35. Shoiebi, A., Khodatars, M., Alizadehsani, R., Ghassemi, N., Jafari, M., Moridian, P., Khadem, A., Sadeghi, D., Hussain, S., Zare, A., et al.: Automated detection and forecasting of covid-19 using deep learning techniques: A review. arXiv preprint arXiv:2007.10785 (2020)
36. Silva, P., Luz, E., Silva, G., Moreira, G., Silva, R., Lucio, D., Menotti, D.: Covid-19 detection in ct images with deep learning: A voting-based scheme and cross-datasets analysis. Informatics in medicine unlocked 20, 100427 (2020)
37. Song, Y., Zheng, S., Li, L., Zhang, X., Zhang, X., Huang, Z., Chen, J., Wang, R., Zhao, H., Chong, Y., et al.: Deep learning enables accurate diagnosis of novel coronavirus (covid-19) with ct images. IEEE/ACM transactions on computational biology and bioinformatics 18(6), 2775–2780 (2021)
38. Talo, M., Baloglu, U.B., Yıldırım, Ó., Acharya, U.R.: Application of deep transfer learning for automated brain abnormality classification using mr images. Cognitive Systems Research 54, 176–188 (2019)
39. Velavan, T.P., Meyer, C.G.: The covid-19 epidemic. Tropical medicine & international health 25(3), 278 (2020)
40. Verschakelen, J., De Wever, W., Matamoros, A.: Computed tomography of the lung: a pattern approach. Journal of Nuclear Medicine 49(1), 164–164 (2008)
41. Voulodimos, A., Doulamis, N., Doulamis, A., Protopapadakis, E.: Deep learning for computer vision: A brief review. Computational Intelligence and neuroscience 2018 (2018)
42. Walvekar, S., Shinde, D., et al.: Detection of covid-19 from ct images using resnet50. In: 2nd International Conference on Communication & Information Processing (ICCIP) (2020)
43. Wang, C., Shi, B., Wei, C., Ding, H., Gu, J., Dong, J.: Initial ct features and dynamic evolution of early-stage patients with covid-19. Radiology of Infectious Diseases 7(4), 195–203 (2020)
44. Wang, H.Y., Li, X.L., Yan, Z.R., Sun, X.P., Han, J., Zhang, B.W.: Potential neurological symptoms of covid-19. Therapeutic advances in neurological disorders 13, 1756286420917830 (2020)
45. Wang, S., Kang, B., Ma, J., Zeng, X., Xiao, M., Guo, J., Cai, M., Yang, J., Li, Y., Meng, X., et al.: A deep learning algorithm using ct images to screen for coronavirus disease (covid-19). European radiology 31(8), 6096–6104 (2021)
46. Wang, W., Xu, Y., Gao, R., Lu, R., Han, K., Wu, G., Tan, W.: Detection of sars-cov-2 in different types of clinical specimens. Jama 323(18), 1843–1844 (2020)
47. wikipedia: Convolutional neural network (2022), https://en.wikipedia.org/wiki/Convolutional_neural_network, last accessed 30 June 2022
48. Wong, H.Y.F., Lam, H.Y.S., Fong, A.H.T., Leung, S.T., Chin, T.W.Y., Lo, C.S.Y., Lui, M.M.S., Lee, J.C.Y., Chiu, K.W.H., Chung, T., et al.: Frequency and distribution of chest radiographic findings in covid-19 positive patients. Radiology (2020)
49. Xing, C., Li, Q., Du, H., Kang, W., Lian, J., Yuan, L.: Lung ultrasound findings in patients with covid-19 pneumonia. Critical Care 24(1), 1–3 (2020)
50. Xu, X., Jiang, X., Ma, C., Du, F., Li, X., Lv, S., Yu, L., Ni, Q., Chen, Y., Su, J., et al.: A deep learning system to screen novel coronavirus disease 2019 pneumonia. Engineering 6(10), 1122–1129 (2020)
51. Yamashita, R., Nishio, M., Do, R.K.G., Togashi, K.: Convolutional neural networks: an overview and application in radiology. Insights into imaging 9(4), 611–629 (2018)
52. Yang, X., He, X., Zhao, J., Zhang, Y., Zhang, S., Xie, P.: Covid-ct-dataset: a ct scan dataset about covid-19. arXiv preprint arXiv:2003.13865 (2020)
53. Yasaka, K., Akai, H., Kunimatsu, A., Kiryu, S., Abe, O.: Deep learning with convolutional neural network in radiology. Japanese journal of radiology 36(4), 257–272 (2018)
54. Zhou, T., Lu, H., Yang, Z., Qiu, S., Hoo, B., Dong, Y.: The ensemble deep learning model for novel covid-19 on ct images. Applied soft computing 98, 106885 (2021)
55. Zhu, N., Zhang, D., Wang, W., Li, X., Yang, B., Song, J., Zhao, X., Huang, B., Shi, W., Lu, R., et al.: A novel coronavirus from patients with pneumonia in china, 2019. New England journal of medicine (2020)