Journal of Engineering and Applied Sciences

MEDWELL PUBLICATIONS SINCE 2000

# Analysis of Covid-19 Based on Deep Learning

Indah Soesanti
*Department of Electrical Engineering and Information Technology, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia*

**Key words:** Covid-19, analysis, deep learning, CT, ResNet

**Corresponding Author:**
Indah Soesanti
*Department of Electrical Engineering and Information Technology, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia*

Page No.: 94-102
Volume: 16, Issue 2, 2021
ISSN: 1816-949x
Journal of Engineering and Applied Sciences


**Abstract:** Coronavirus disease 2019 (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was first identified in December 2019. The disease can be detected by using Computed Tomography (CT) medical image analysis. The methods used for Covid-19 detection are based on Deep Learning. Deep Learning Model used are 3D ResNet34, VGG, AlexNet, VGG-16,VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101 and Xception. The researchers use public datasets from patient data Covid-19 and Non-Covid-19. One of the researchers applies the methods for cross dataset. The results from the research show that Deep Learning has high performance and can solve the problem of Covid-19 image classification and Covid-19 detection.

## INTRODUCTION

Coronavirus disease 2019 (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was first identified in December 2019. The coronavirus was first discovered in Wuhan, China. The virus has infected a total of 8.3M cases (December 2020). Reverse Transcription Polymerase Chain Reaction (RT-PCR) testing of respiratory samples is currently the gold standard for COVID-19 diagnosis. However, examination using this method is time-consuming and has a high false-negative rate and low sensitivity[1].

The disease can be detected by using Computed Tomography (CT) medical image analysis. The accuracy of the diagnosis of COVID-19 by Chest scans strongly depends on experts[2] and deep learning techniques have been studied as a tool to automate and help with the diagnosis[3-7].

Detection using CT images can distinguish COVID-19 from pneumonia. Several studies have been conducted to develop CAD systems used to detect COVID-19 based on CT-scan results[8-15].

## MATERIALS AND METHODS

Ouyang *et al*.[8] use a dual-sampling attention network method in classifying COVID-19 and CAP infection (Pneumonia) through 3D lung CT-scan images. The proposed method, dual-sampling was used to classify 4982 chest CT-scan images from 3645 patients with 3389 images of COVID-19 and 1593 images of CAP sufferers. The Dual-sampling attention network is a combined method between 3D ResNet34 and uniform sampling with 3D ResNet34 and size-balanced sampling. The proposed method can identify images of COVID-19 patients with an AUC value of 0.944, accuracy of 87.5%, sensitivity of 86.9%, specificity of 90.1% and F1-score of 82.0%.

The supervised deep learning method is used by Hu *et al*.[1] to detect areas infected with COVID-19 automatically using CT-scan data of the patient's chest cavity obtained from various sources. Data from The Cancer Imaging Archive (TCIA) consisting of 60 3D CT-scan of the patient's lungs was used as a dataset in the classification using a VGG-inspired architecture with a configuration that increases the depth of the CNN network using a small convolutional filter in the presence of non-linearity between its convolutional layers. The proposed method can identify images of COVID-19 patients with an AUC value of 0.923, an accuracy of 89.2%, a sensitivity of 88.6% and a specificity of 87.6%.

Farooq and Hafeez[4] also develop a method that can rapidly examine COVID- 19 through 3D images from CT scans[4]. The study used CT scan images from 4657 patients from various hospitals, consisting of 936 normal images, 2406 ILD and 1315 COVID-19 as the dataset. The proposed classification method uses two 3D-ResNETS which are combined into a model. The proposed method was able to provide an accuracy of 93.3%, a sensitivity of 87.6 and 95.5%.

The deep learning-based CAD system was developed by Ali Abasian, etc., to classify COVID-19 infections from other types of pneumonia. The 1020 CT-scan images (510 COVID-19 and 510 non-COVID-19) from 108 patients with COVID-19 and 86 patients with other types of pneumonia were used to train 10 well-known neural networks. The ten networks used are AlexNet, VGG-16, VGG-19, SquezeeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101 and Xception. The best performance is shown by ResNet-101 and Xception architecture. ResNet-101 can differentiate COVID-19 infection from other types of pneumonia with an AUC value of 0.994 (100% sensitivity, 99.02% specificity and 99.51% accuracy). Xception produces an AUC of 0.994 (sensitivity 98.04%, specificity 100% and accuracy 99.02%).

Besides, developing a classification method for detecting COVID-19 through CT-scan images, some researchers develop a dataset as a standard dataset to detect COVID-19. Misztal *et al*.[9] study to createa public dataset of CT images and radiographs of the lungs to increase efficiency in differentiating COVID-19 from other types of pneumonia and healthy[3]. The new dataset being developed is named COVID-19 CT and Radiograph Image Data Stock which consists of 11,279 CT lung data and 6,250 radiographic data. The method of forming a new dataset produces the highest accuracy with the use of WideResNet-50 on CT data which is 78%. While for radiograph data, the highest accuracy is obtained by using ResNet-18, ResNet-50, DenseNet 169 and WideResNet-50 by 50%. The AUC for the two data sources were 0.74 and 0.97, 0.98, 0.97, and 0.97, respectively. These results were obtained using binary classifiers trained on COVID-19 CT&R.

The application of transfer learning in several models used by Horry *et al*.[16] for the identification of COVID-19 based on Lung image analysis. Three types of medical images of the lungs are used. There are X-ray, Ultrasound (USG) and CT images. The images are obtained and taken from various sources with image sizes and quality variance. They use 2 scenarios in the research. There are: identification of pneumonia (COVID-19 and others) from normal lung images and identification of COVID-19 from non-COVID-19 pneumonia.

The original images are pre-processed by resizing and quality enhancement. The N-CLAHE algorithm is used to improve image quality. This algorithm can increase detail, texture and brightness. The image augmentation is created such as horizontal flip, horizontal vertical shift and rotation. Image data is divided into 80:20 for each image type.

The first experiment is done by implementing transfer learning which is using parameter initialization from a model that had been trained on image Net data. The models used are VGG16, VGG19, ResNet50V2, InceptionV3, Xception, Inception ResNet V2, NasNet Large and DenseNet121. These models are used as the base model which beadded with a pooling layer, FC layer and output layer. The FC layer has 2 neurons. Hyperparameters are used in the research are learning rate, batch size, neurons per hidden layer and dropout rate. All models are trained 5 times with 100 epochs. The result shows that VGG19 has better performance than other models. The model also shows better performance with various hyperparameters. More complex models tend to be overfitting at the start of the epoch and some do not converge at all. The ultrasound images performed better than the others.

In the second experiment, they adjust the hyperparameter for VGG19 to obtain optimal results. Hyperparameters that are used are learning rate, batch size, neurons per hidden layer, and dropout rate. The best results are obtained in the model for ultrasound images with scenario 2. There are learning-rate = 10-5, batch size = 2, neurons per hidden layer = 64 and dropout rate = 0.2 with an epoch of 100. The performance ofthis model is successfully approaching the ideal model.

The VGG19 model shows high performance for X-ray and CT images, especially for ultrasound images. The use of N-CLAHE for pre-processing helps in equalizing the quality of the image. The use of multiple image types to identify COVID-19 helps improve performance on the model.

The method to perform classification in patients infected with COVID-19 and patients who are not infected based on chest CT images automatically to reduce subjectivity in decision making during the diagnosis process. Figure 1 shows the chest CT changes in a COVID-19 patient at 5 days. Chest CT images show a progression of pneumonia with mixed Ground-Glass Opacities (GGO) and linear opacities in the subpleural areas.

The 3-DCNN can classify the pulmonary artery on CT images with high accuracy values. In other studies, the Adaptive Neuro-Fuzzy Inferences Systems (ANFIS) is used to increase the classification rate. The GCNN method can be used to classify patients infected with COVID-19. By obtaining good results in previous studies, it is expected that the results can be further improved by using a more efficient feature extraction using a variant of ResNet. Also, hyper-tuning in the Deep Learning model can be used in the Transfer Learning model. Therefore, the novel Deep Transfer Learning (DTL) was developed to classify COVID-19 patients[21]. In this study, there are several novelties offered in carrying out the COVID-19 classification model. The novelties are: The Deep Transfer Learning model is used for the COVID-19 classification process which refers to the patient's chest CT image, There is Top-2 Smooth Loss Function which is used to reduce noise, Deep transfer learning models are trained to perform analysis on chest CT and expert analysis is carried out as a comparison for the results that have been achieved.

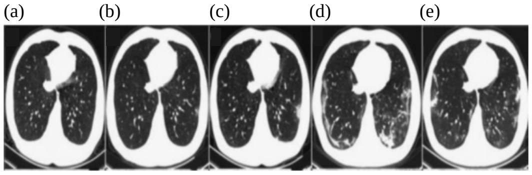


Fig. 1(a-e): Chest CT in COVID-19 patients days 1-5[6]

In the study of the Transfer Learning with Deep Residual Networks, ResNet-50 architecture was used to extract values from chest CT images. ResNet-50 is an architecture from CNN that introduces a new concept, shortcut connections. In this concept, the input from the previous layer is the input to the output of that layer.

In the research, the feature map is processed into the fully connected layer to carry out the prediction process assisted by the softmax activation function. Some of the parameters that are regulated are bias initialization = 1.0, normally distributed, with learning rate = 0.02, momentum of 0.8. The gradient threshold is 1.0 by using the MCXENT function as a loss function.

In the research, images are collected from various datasets. There are 415 images of patients infected with COVID-19 and 439 images of normal patients. From the available images, it is determined that 60% of the dataset is used as training data and 40% of the dataset is used as testing for the COVID-19 classification. From 60% of the training data, 10% of data is used for validation. The 10-fold cross-validation is used to prevent overfitting problems. Deep Transfer Learning (DTL) was used to build a classification model for patients infected with COVID-19 with epoch 110. The analysis of the training and validation of the DTL and GCNN models shows good results. The excellent value generated compared to conventional methods makes the proposed model a reliable alternative to various testing kits by providing fast results.

Figure 2 shows the flowchart of multi-task learning in deep neural networks used by Amyar *et al*.[17]. In this study, the methods based on deep Learning used in COVID-19 analysis are reviewed and shown in Table 1.

Table 1: The significant improvement of the proposed classification model

| Researchers | Objectives | Dataset | Proposed method | Results |
|---|---|---|---|---|
| Ouyang *et al*.[8] | Develop a dual-sampling attention network method in classifying COVID-19 and CAP infection (Pneumonia) in 3D lung CT-scan images | The 4982 chest CT-scan images from 3645 patients with 3389 images of COVID-19 and 1593 images of CAP sufferers. Data were obtained from Tongji Hospital of Huazhong University of Science and Technology, Shanghai Public Health Clinical Center of Fudan University, the Second Xiangya Hospital of Central South University, the Third Hospital of Jilin University, Ruijin Hospital of Shanghai Jiao Tong University School of Medicine, Hangzhou First People's Hospital of Zhejiang University, the Beijing Chaoyang Hospital of Capital Medical | Dual-sampling attention network consisting of a combination of 3D ResNet34 and uniform sampling with 3D ResNet34 and size-balanced sampling. The use of 3D ResNet34 is done to improve the quality of attention maps produced based on higher resolution feature maps. Meanwhile, the use of size-balanced sampling was carried out to repeat data sampling for COVID-19 cases with small infections and also CAP cases with large infections in each minibatch during the training process. By using size-balanced sampling, | The proposed method can identify images of COVID-19 patients with an AUC value of 0.944, accuracy of 87.5%, sensitivity of 86.9%, specificity of 90.1% and F1-score of 82.0% |

Table 1: Continue

| Researchers | Objectives | Dataset | Proposed method | Results |
|---|---|---|---|---|
| | | | we can obtain more attention in minority classes and eliminate bias in the area of infection between COVID-19 and CAP patients, so as to overcome the overfitting of these minority classes. The use of uniform sampling can be used to study the feature representation of the original data distribution in a reliable way | |
| Hu *et al*.[1] | To develop a supervised deep learning method to automatically detect areas infected with COVID-19 using CT-scan data of the patient's chest cavity obtained | Data from The Cancer Imaging Archive (TCIA) consisting of 60 3D CT-scan data of patient's lungs | VGG-inspired architecture with a configuration that increases CNN network depth using a small convolutional filter with non-linearity between the convolutional layers. Rationale for choosing the method Because the proposed method can be used to minimize the need for manual CT-scan image labeling but it can still provide accurate infection detection results and can distinguish COVID-19 cases from non-COVID-19 cases | The proposed method can identify images of COVID-19 patients with an AUC value of 0.923, an accuracy of 89.2%, a sensitivity of 88.6% and a specificity of 87.6% |
| Miztal *et al*.[9] | To create a public dataset of CT images and radiographs of the lungs so as to increase efficiency in differentiating COVID-19 from other types of pneumonia and from healthy lungs | COVID-19 CT and Radiograph Image Stock data consisting of 11,279 CT lung data and 6,250 radiographic data | Classification is done using a variety of deep learning architectures, namely ResNet-18, ResNet-50, DenseNet-169, WideResNet-50 and DenseNet-121 | The method of forming a new dataset produces the highest accuracy with the use of on CT data which is 78%. While for radiograph data, the highest accuracy is obtained by using ResNet-18, ResNet-50, DenseNet169 and WideResNet-50 by 50%. The AUC for the two data sources were 0.74 and 0.97, 0.98, 0.97 and 0.97, respectively. These results were obtained using binary classifiers trained with the COVID-19 CT and Radiograph image Data stock and evaluated using the multiclass COVID-19 CT and radiograph image data stock |
| Wang *et al*.[10] | To develop a method that can quickly examine COVID-19 through 3D images from CT scans | CT scan images of 4657 patients from various hospitals, consisting of 936 normal images, 2406 ILD and 1315 COVID-19 | Using two 3D-ResNETS combined into one model. Because the proposed method is implemented as a binary classifier and can identify COVID-19 from ILD caused by other | The proposed method was able to provide an accuracy of 93.3%, a sensitivity of 87.6 and 95.5% |

Table 1: Continue

| Researchers | Objectives | Dataset | Proposed method | Results |
|---|---|---|---|---|
| | | | viruses. In addition, the classifier that is designed can also predict whether a given CT-scan image contains pneumonia. In addition, the proposed method is easier to implement because it only requires weak image-level labels and fewer hyper-parameters during training. So that, the method can collect sufficient samples in a short time | |
| Ardakani *et al*.[11] | To develop a deep learning- based CAD system to classify COVID-19 infections from other types of pneumonia | 1020 CT-scan images (510 COVID-19 and 510 non-COVID-19) from 108 patients with COVID-19 and 86 patients with other types of pneumonia | Comparing the 10 most widely used CNN methods, namely AlexNet, VGG-16, VGG-19, SquezeeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101 and Xception. To find out the best CNN architecture that can be used to diagnose COVID-19 | The best performance is shown by ResNet-101 and Xception architecture. ResNet-101 can differentiate COVID-19 infection from other types of pneumonia with an AUC value of 0.994 (100% sensitivity, 99.02% specificity and 99.51% accuracy) Whereas Xception produces an AUC of 0.994 (sensitivity 98.04%, specificity 100% and accuracy 99.02%) |
| Amyar *et al*.[17] | To detect the severity of pneumonia and follow up on COVID-19 patients | The dataset used 1369 patients included 449 patients with COVID-19, 425 normal patients, 98 with lung cancer patients and 397 with various types of pathology | Multitask deep learning to identify COVID-19 patients with three lessons, namely: segmentation, classification and reconstruction | The research results of this study show a very high accuracy than other models of segmentation of 88% and classification of 97% |
| Xu *et al*.[15] | This study aims to form an initial screening model to distinguish COVID-19 from IAVP and healthy cases through CT images of the lungs using deep learning techniques | In this study, 618 CT samples were collected: 219 samples from 110 COVID-19 patients (mean age 50 years; 63 (57.3%) male patients); 224 samples of 224 samples of patients with IAVP (mean age 61 years; 156 (69.6%) male patients) and 175 samples of 175 healthy cases (mean age 39 years; 97 (55.4%)) male patient). All CT samples contributed from three designated COVID-19 hospitals in Zhejiang Province, China | 3D CNN segmentation model+ ResNet18 | This research presents a new method that can detect COVID-19 automatically through deep learning technology. A model with a location-attention mechanism can classify COVID- 19, IAVP and other cases with an overall accuracy rate of 86.7% |
| Zheng *et al*.[18] | The aim was to investigate the potential of a deep learning- based model for automatic COVID-19 detection of chest CT volumes using patient level labels | Data from 540 patients (mean age, 42.5±16.1 years; range, 3-81 years, 226 men, 314 women) were enrolled in the study, including 313 patients(mean age, 50.7±14.7 years; range, 8-81 years; men 138 women 175) with clinically diagnosed COVID-19 (COVID-19 positive group) and 229 patients (mean age, 31.2±10.0 years; range, 3-69 years old; male 88, female 141) without COVID-19 | Deep learning | There are still some limitations in this study.First, network design and training can be further improved. For example, the UNet model for lung segmentation does not use temporal information and is trained using imperfect ground-truth masks which can be scaled up using a 3D segmentation network and adopting expert ground-truth |

Table 1: Continue

| Researchers | Objectives | Dataset | Proposed method | Results |
|---|---|---|---|---|
| | | (COVID-19 negative group) | | annotations. Second, the data used in this study came from one hospital and cross- center validation was not carried out. Third, when diagnosing COVID-19 the algorithm works in a black box way because the algorithm is based on deep learning and the explanation is still at an early stage |
| Zhou *et al*.[19] | This article focuses on the rapid detection of COVID-19 | Transfer learning was used to initialize model parameters and pretrain three deep convolutional neural network models: AlexNet, GoogleNet, and ResNet | Ensemble deep learning model | The EDL_COVID model produces a faster time to classify, namely 342.92 s and has better accuracy than other individual classifications (Alexnet_softmax, Googlenet_ softmax and Resnet_ softmax) by obtaining an accuracy of 99.05% |
| Silva *et al*.[20] | To produce an efficient model and extend the Efficient Net Family of deep artificial neural networks along with a data augmentation process and transfer learning | SARS-CoV-2 CT-scan dataset and COVID-CT | Efficient Deep Learning Artificial Neural Networks | A model for the detection of COVID-19 patterns in CT images, EfficientCovidNet. The cross-dataset approach is of paramount importance for the methods aiming to detect COVID-19 in CT images, since, the approach resembles a real scenario and unveils the limitations of the methods (for instance, the accuracy drops from 87.68-56.16% in this scenario for the COVID-CT test set) |
| Pathak *et al*.[21] | Dalam penelitian ini, teknik deep transfer learning digunakan untuk melakukan klasifikasi Pasien yang terinfeksi COVID-19. Selain itu, fungsi smooth loss 2 teratas dengan cost-sensitive attributes adalah juga digunakan untuk menangani handle noisy and imbalanced COVID-19 dataset kind of problems | 413 COVID-19 (+) images and 439 images of normal or pneumonia infected patients images | Deep Transfer Learning Transfer Learning using ResNet CNN | Model yang diajukan berhasil mendapatkan akurasi pada data latih dan data uji sebesar 96.2264 and 93.0189% |

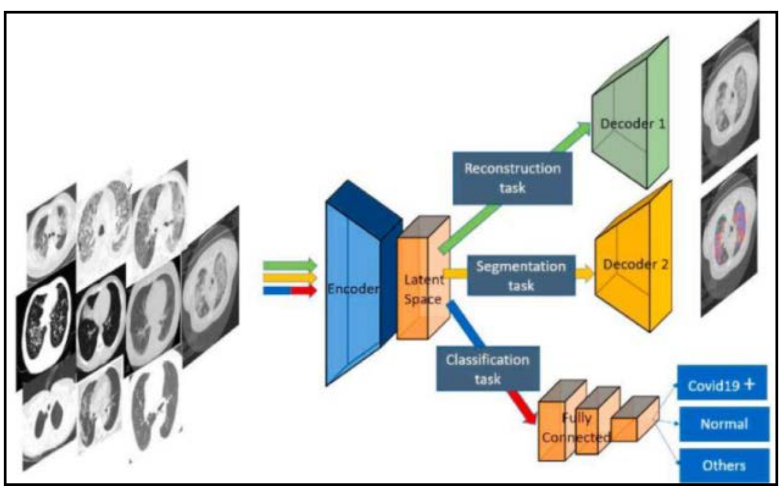


Fig. 2: The research flowchart of the proposed method[17]

## RESULTS AND DISCUSSION

In its development, there are several deep learning models that can be used to solve medical image classification problems. Deep Learning models that have been developed can be grouped into several model families such as AlexNet, VGG Nets, Inception-based Nets, ResNets, MobileNets, DenseNets and NASNets on their different architectures[22]. In recent years, modified and hybrid models have developed[23]. The aim is to improve the performance of the base model by proposing novelty in layers and filters such as Sparse Shift Filter[24], Asymmetric Block Convolution[25], Adder Network[26], Virtual Merging[27], Discrete Wave Transformation[28] and HetConv[29], etc. Several recent substantial models have been developed which are based on the basic model such as Res2Net[30] and Wide ResNet using the ResNet Model. Log Dense Net and Sparse Net[31] are based on the DenseNet Model. The development on the other hand is to combine several basic models that are owned to produce a number of hybrid models including AOGNet[32], PNASNet[33], AmoebaNet[34], DPN[35], HCGNet[36], GCNet[36], ThiNet[37] and SKNet[38].

## CONCLUSION

Many deep learning-based methods are used for Covid-19 analysis including several models, there are 3D ResNet34, VGG, AlexNet, VGG-16, VGG-19, SqueezeeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101 and Xception. Many studies have been conducted in analyzing image data from public datasets which are Covid-19 and Non-Covid-19 patient data.

One of the researchers uses the cross dataset method. The results of the many studies that have been conducted show that some deep learning has high performance and can solveand can solve the problem of the classification of Covid-19 images and detection of Covid-19.

However, it is still necessary to develop a method in the form of a modified model or hybrid model, so that, it can provide the optimal model to analyze the medical image of Covid-19.

## ACKNOWLEDGMENT

The researcher gratefully acknowledges the contribution from the Ministry of Research and Technology, Republic of Indonesia, for funding this research.

## REFERENCES

01. Hu, S., Y. Gao, Z. Niu, Y. Jiang and L. Li *et al*., 2020. Weakly supervised deep learning for Covid-19 infection detection and classification from ct images. IEEE Access, 8: 118869-118883.
02. Ng, M.Y., E.Y. Lee, J. Yang, F. Yang and X. Li *et al*., 2020. Imaging profile of the Covid-19 infection: Radiologic findings and literature review. Radiol. Cardiothorac. Imaging, Vol. 2, No. 1. 10.1148/ryct.2020200034
03. Hemdan, E.E.D., M.A. Shouman and M.E. Karar, 2020. Covidx-net: A framework of deep learning classifiers to diagnose Covid-19 in x-ray images. Comput. Vision Pattern Recognit., Vol. 1,
04. Farooq, M. and A. Hafeez, 2020. Covid-resnet: A deep learning framework for screening of Covid19 from radiographs. Electr. Eng. Syst. Sci., Vol. 1,
05. Abbas, A., M. Abdelsamea and M. Gaber, 2020. Classification of Covid-19 in chest X-ray images using DeTraC deep convolutional neural network. BMJ., Vol. 1, 10.1101/2020.03.30.20047456
06. Wang, L., Z.Q. Lin and A. Wong, 2020. Covid-net: A tailored deep convolutional neural network design for detection of Covid-19 cases from chest x-ray images. Sci. Rep., 10: 1-12.
07. Luz, E.J.D.S., P.L. Silva, R. Silva, L. Silva, G. Moreira and D. Menotti, 2020. Towards an effective and efficient deep learning model for Covid-19 patterns detection in X-ray images. CoRR., Vol. 1,
08. Ouyang, X., J. Huo, L. Xia, F. Shan and J. Liu *et al*., 2020. Dual-sampling attention network for diagnosis of Covid-19 from community acquired pneumonia. IEEE. Trans. Med. Imaging, 39: 2595-2605.
09. Misztal, K., A. Pocha, M. Durak-Kozica, M. Wator, A. Kubica-Misztal and M. Hartel, 2020. The importance of standardization-Covid-19 CT & radiograph image data stock for deep learning purpose. Comput. Biol. Med., Vol. 127, 10.1016/j.compbiomed.2020.104092
10. Wang, J., Y. Bao, Y. Wen, H. Lu and H. Luo *et al*., 2020. Prior-attention residual learning for more discriminative Covid-19 screening in CT images. IEEE. Trans. Med. Imaging, 39: 2572-2583.
11. Ardakani, A.A., A.R. Kanafi, U.R. Acharya, N. Khadem and A. Mohammadi, 2020. Application of deep learning technique to manage Covid-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. Comput. Biol. Med., Vol. 121, 10.1016/j.compbiomed.2020. 103795
12. Ulhaq, A., A. Khan, D. Gomes and M. Pau, 2020. Computer vision for Covid-19 control: A survey. Image Video Process., Vol. 1,
13. Born, J., G. Brandle, M. Cossio, M. Disdier, J. Goulet, J. Roulin and N. Wiedemann, 2020. POCOVID-Net: Automatic detection of Covid-19 from a new lung ultrasound imaging dataset (POCUS). ISMB., Vol. 1,

14. Chen, J., L. Wu, J. Zhang, L. Zhang and D. Gong *et al*., 2020. Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: A prospective study. MedRxiv, Vol. 1, 10.1101/2020.02.25.20021568
15. Xu, X., X. Jiang, C. Ma, P. Du and X. Li *et al*., 2020. A deep learning system to screen novel coronavirus disease 2019 pneumonia. Engineering, 6: 1122-1129.
16. Horry, M.J., S. Chakraborty, M. Paul, A. Ulhaq, B. Pradhan, M. Saha and N. Shukla, 2020. COVID-19 detection through transfer learning using multimodal imaging data. IEEE Access, 8: 149808-149824.
17. Amyar, A., R. Modzelewski, H. Li and S. Ruan, 2020. Multi-task deep learning based CT imaging analysis for COVID-19 pneumonia: Classification and segmentation. Comput. Biol. Med., Vol. 126, 10.1016/j.compbiomed.2020.104037
18. Zheng, C., X. Deng, Q. Fu, Q. Zhou and J. Feng *et al*., 2020. Deep learning-based detection for Covid-19 from chest CT using weak label. MedRxiv., Vol. 1, 10.1101/2020.03.12.20027185
19. Zhou, T., H.L. Lu, Z. Yang, S. Qiu, B.Q. Huo and Y. Dong, 2020. The ensemble deep learning model for novel Covid-19 on CT images. Applied Soft Comput., Vol. 1, 10.1016/j.asoc.2020.106885
20. Silva, P., E. Luz, G. Silva, G. Moreira, R. Silva, D. Lucio and D. Menotti, 2020. COVID-19 detection in CT images with deep learning: A voting-based scheme and cross-datasets analysis. Inf. Med. Unlocked, Vol. 20, 10.1016/j.imu.2020.100427
21. Pathak, Y., P.K. Shukla, A. Tiwari, S. Stalin, S. Singh and P.K. Shukla, 2020. Deep transfer learning based classification model for Covid-19 disease. IRBM., Vol. 1, 10.1016/j.irbm.2020.05.003
22. Kornblith, S., J. Shlens and Q.V. Le, 2019. Do better imagenet models transfer better?. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, June 16-20, 2019, IEEE, California, USA., pp: 2661-2671.
23. Yang, C., Z. An, H. Zhu, X. Hu and K. Zhang *et al*., 2020. Gated convolutional networks with hybrid connectivity for image classification. AAAI., 34: 12581-12588.
24. Chen, W., D. Xie, Y. Zhang and S. Pu, 2019. All you need is a few shifts: Designing efficient convolutional neural networks for image classification. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, June 16-20, 2019, IEEE, Long Beach, California, pp: 7241-7250.
25. Ding, X., Y. Guo, G. Ding and J. Han, 2019. Acnet: Strengthening the kernel skeletons for powerful CNN via asymmetric convolution blocks. Proceedings of the IEEE International Conference on Computer Vision, October 27, 2019, IEEE, Seoul, South Korea, pp: 1911-1920.
26. Chen, H., Y. Wang, C. Xu, B. Shi, C. Xu, Q. Tian and C. Xu, 2020. AdderNet: Do we really need multiplications in deep learning?. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, June 19, 2020, IEEE, California, USA., pp: 1468-1477.
27. Chen, Z., J. Zhang, R. Ding and D. Marculescu, 2020. Vip: Virtual pooling for accelerating CNN-based image classification and object detection. Proceedings of the IEEE Winter Conference on Applications of Computer Vision, March 1-5, 2020, IEEE, Colorado, USA., pp: 1180-1189.
28. Li, Q., L. Shen, S. Guo and Z. Lai, 2020. Wavelet integrated CNNs for noise-robust image classification. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, June 13-19, 2020, IEEE, Seattle, Washington State, pp: 7245-7254.
29. Singh, P., V.K. Verma, P. Rai and V.P. Namboodiri, 2019. Hetconv: Heterogeneous kernel-based convolutions for deep CNNs. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, June 15-20, 2019, IEEE, Long Beach, California, USA., pp: 4835-4844.
30. Gao, S., M.M. Cheng, K. Zhao, X.Y. Zhang, M.H. Yang and P.H. Torr, 2019. Res2net: A new multi-scale backbone architecture. IEEE. Trans. Pattern Anal. Mach. Intell., Vol. 1, 10.1109/TPAMI.2019.2938758
31. Zhu, L., R. Deng, M. Maire, Z. Deng, G. Mori and P. Tan, 2018. Sparsely Aggregated Convolutional Networks. In: Computer Vision-ECCV 2018, Ferrari, V., M. Hebert, C. Sminchisescu and Y. Weiss (Eds.)., Springer, Berlin, Germany, pp: 192-208.
32. Li, X., X. Song and T. Wu, 2019. AOGNets: Compositional grammatical architectures for deep learning. Proceedings of the 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 15-20, 2019, Long Beach, California, USA., pp: 6213-6223.
33. Liu, C., B. Zoph, M. Neumann, J. Shlens and W. Hua *et al*., 2018. Progressive neural architecture search. Proceedings of the European Conference on Computer Vision (ECCV), September 8-14, 2018, Munich, Germany, pp: 19-34.
34. Real, E., A. Aggarwal, Y. Huang and Q.V. Le, 2019. Regularized evolution for image classifier architecture search. Proceedings of the AAAI Conference on Artificial Intelligence, July 23, 2019, AAAI, California, USA., pp: 4780-4789.

35. Chen, Y., J. Li, H. Xiao, X. Jin, S. Yan and J. Feng, 2017. Dual path networks. Adv. Neural Inf. Process. Syst., 30: 4467-4475.
36. Cao, Y., J. Xu, S. Lin, F. Wei and H. Hu, 2019. GCNet: Non-local networks meet squeeze-excitation networks and beyond. Proceedings of the IEEE/CVF International Conference on Computer Vision Workshop (ICCVW), October 27-28, 2019, IEEE, Seoul, South Korea, pp: 1971-1980.
37. Luo, J., H. Zhang, H. Zhou, C. Xie, J. Wu and W. Lin, 2019. ThiNet: Pruning CNN filters for a thinner net. IEEE. Trans. Pattern Anal. Mach. Intell., 41: 2525-2538.
38. Li, X., W. Wang, X. Hu and J. Yang, 2019. Selective kernel networks. Proceedings of the 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 15-20, 2019, IEEE, Long Beach, California, USA., pp: 510-519.