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Multilevel depth-wise context attention network with atrous mechanism for segmentation of COVID19 affected regions

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Abstract
Severe acute respiratory syndrome coronavirus (SARS-CoV-2) also named COVID-19, aggressively spread all over the world in just a few months. Since then, it has multiple variants that are far more contagious than its parent. Rapid and accurate diagnosis of COVID-19 and its variants are crucial for its treatment, analysis of lungs damage and quarantine management. Deep learning-based solution for efficient and accurate diagnosis to COVID-19 and its variants using Chest X-rays, and computed tomography images could help to counter its outbreak. This work presents a novel depth-wise residual network with an atrous mechanism for accurate segmentation and lesion location of COVID-19 affected areas using volumetric CT images. The proposed framework consists of 3D depth-wise and 3D residual squeeze and excitation block in cascaded and parallel to capture uniformly multi-scale context (low-level detailed, mid-level comprehensive and high-level rich semantic features). The squeeze and excitation block adaptively recalibrates channel-wise feature responses by explicitly modeling inter-dependencies between various channels. We further have introduced an atrous mechanism with a different atrous rate as the bottom layer. Extensive experiments on benchmark CT datasets showed considerable gain (5%) for accurate segmentation and lesion location of COVID-19 affected areas.

Keywords COVID19 · CT · Atrous mechanism · Segmentation · Depth-wise · Channel-wise CNN

1 Introduction

Coronavirus infection, a severe acute respiratory syndrome, is an ongoing pandemic that the world has been facing since December 2019. It is life threatening and most contiguous virus with high infectivity and extreme lethality. Up to 20th September 2021, 219 million COVID cases have been reported with 4.55 million deaths across 216 countries and territories worldwide. US and India are the leading affected countries with 42.1/0.674 million and 33.4/0.445 million reported cases/death. Figure 1 shows the recent death and recovery rate. Variants of COVID-19, such as Delta, Delta-2 and mu, are far more aggressive than the original COVID, and its rapid spread was blamed for strict tier four mixing rules for millions of people and much harsher restrictions and travel bans. COVID-19 is a novel beta-corona virus that affects different people with various symptoms and shares similarities with Middle East Respiratory Syndrome (MERS) and SARS viruses that were previously responsible for endemics in 2012 and 2003, respectively.

To stop the spread of COVID-19, rapid, robust and accurate, testing protocol plays very role. Clinically, Reverse Transcription Polymerase Chain Reaction (RT-PCR) is gold standard for COVID detection and being actively used as standard practice for COVID screening. However, strict testing requirements for testing environments and

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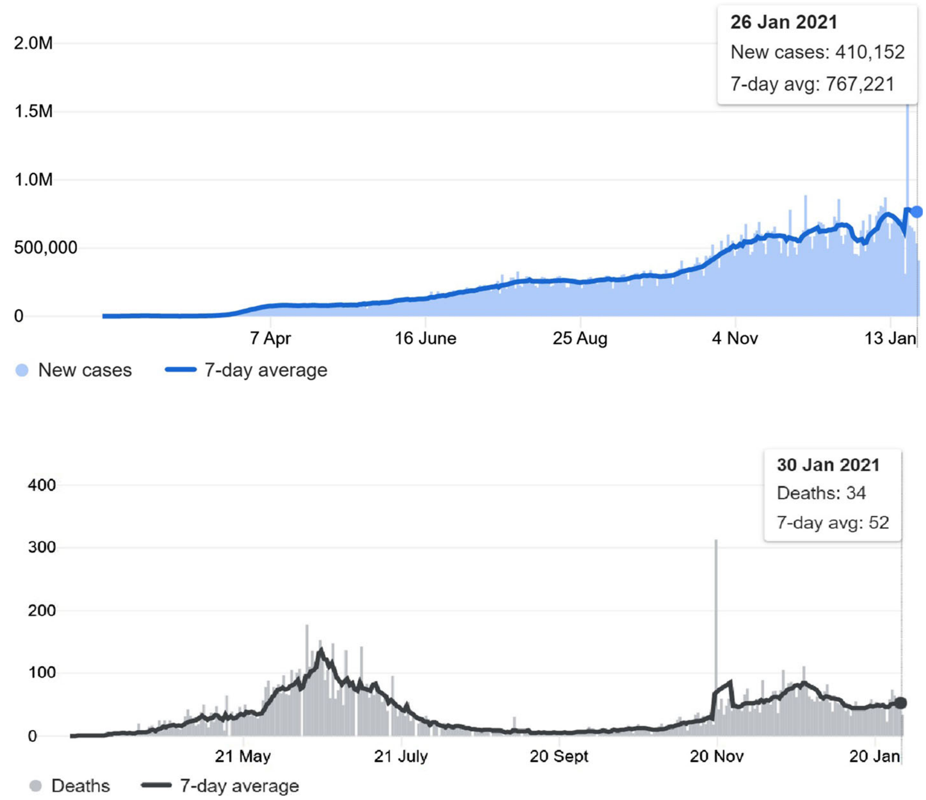


Fig. 1 Cumulative known cases per million since 100th case and deaths per million since 1st death recorded[1]

equipment shortage limit the accurate and fast screening of COVID suspected patients [18]. Inappropriate sample collection and other parameters such as storage, transfer, purification and processing also reduced the sensitivity of RT-PCR testing. Thus, RT-PCR has high false-negative rates, and patient is required to quarantine himself until he receive the test result which is typical 24 h sample-to-result turnaround time. Thus, it dramatically limited our ability to screen suspected patients rapidly.

Radiological image analysis such as CT, X-rays and MRI has shown itself as an alternative approach for the efficient and accurate diagnosis of COVID related infection and evaluation of respiratory related complications. It provides the diagnosis and provides considerable knowledge for the disease progression, evolution and follow-up assessment. CT-based analysis is more effective due to high spatial resolution and is able to detect even smaller lesions with high degree of sensitivity. Manual analysis of lung infections is a labor-intensive, tedious, time-consuming and time-consuming task. It is also a highly subjective (inter and intra radiologist variabilities) task as often influenced by radiologist experience and bias. Thus, an automatic classification of affected areas is highly desirable for the early diagnosis of COVID. However, identifying COVID-19 affection areas from radiology images is challenging for several reasons, i.e., the huge variations in size and position of lesions. In addition to this, the infection may have various complex appearances such as consolidation, reticulation, ground-glass opacity, etc. Furthermore, the ambiguous boundary and irregular shape of the lesion are further complicated and difficult to segment.

Automated segmentation of COVID affected area will ease radiologist and clinicians' work by making the diagnoses reliable. However, it involves several challenges such as (i) segmentation of infected area is sensitive to several intrinsic factors i.e., intensity inhomogenity and huge variation in infections, physical appearance with the proximity of infection and texture of infected regions and segmentation of affected area in lungs need to process more discriminative information. Recently, deep learning has been extensively applied in medical image analysis [14, 21]. Several methods have been presented to analyze the Chest images (CT and MRI) to detect patients infected with COVID-19 [8, 20, 22, 23, 29]. Fan et al. aggregated high-level features using parallel partial decoder and presented semi-supervised lung infection segmentation deep network (Inf-Net) for segmentation of infected regions from CT images [8]. To enhance the representation, explicit edge and implicit reverse attention is used that model the infection boundaries. Wang et al. presented noise-robust dice loss-based Pneumonia Lesion segmentation ensemble network (COPLE-Net) for segmentation of COVID affected areas [29]. COPLE-Net and noise-robust Dice loss are combined through an ensembling network, and an exponential moving average of the student model is used as a teacher model that is updated adaptively by suppressing the student network to exponentially moving average in case the student network has larger training loss. Li et al. presented COVID-19 detection neural network (COVNet) for COVID lesion segmentation from CT exams [15]. U-net and its variants are the most widely used encoder-decoder network for segmentation since it captures high and low-level features through the encoder and semantic features through the decoder. Chen et al. applied UNet+ + for the detection of COVID suspected lesion [5]. Hu et al. presented squeeze and excitation blocks to improve the representational of the network by modeling the inter-dependencies between the channels of its convolutional features [13]. Similarly, Roy et al. fused spatial and channel SE blocks feature by re-calibrating the feature representation channel-wise and spatially [25].

To address the challenges mentioned earlier, in this work, we propose a depth-wise multilevel feature deep neural network for the diagnosis of COVID-19 lesions. The network consists of multiple blocks that uniformly scale all dimensions (depth, width and resolution) and perform multilevel feature embedding. Unlike traditional CNN methods, the network arbitrarily scales the dimensions with a fixed set of scaling coefficients in each block followed by multilevel feature fusion by aggregating the high- level features to combine the contextual information. The inclusion of depth-wise components and squeeze-and-excitation results in better performance by capturing more receptive fields than traditional convolutional layers; however, the parameters are almost the same. The key contributions of this work are.

- Balancing the width, depth and resolution of network can results in better feature representation, thus, we present depth-wise multilevel feature fusion by aggregating the high-level features to combine the contextual information.
- Each encoder/decoder in the proposed framework consist of 3D depth-wise and 3D residual squeeze and excitation block in cascaded and parallel as well to capture uniformly multi-scale context (low-level detailed, mid-level comprehensive and high-level semantic features).
- Introduce a novel multilevel depth deep framework aided with atrous mechanism with different atrous rate as bottom layer to extracts rich semantic information for an accurate and efficient automated detection of COVID infection.
- Squeeze and excitation block adaptively recalibrates channel-wise feature responses by explicitly modeling inter-dependencies between different channels.
- Performed extensive experiments on benchmark CT dataset that demonstrate the effectiveness of proposed framework in comparison to cutting-edge methods especially based on transfer learning.

The rest of the paper is organized as follows: In Sect. 2, we present the recent development on COVID lesion identification, followed by proposed depth-wise multilevel deep network. In Sect. 4, we present experimental analysis and evaluation of proposed framework on benchmark dataset.

2 Related work

Recently, deep learning has been extensively use for medical image analysis, and several deep learning methods have presented to analyze the Chest images (Ultrasound, CT and MRI) for the detection of patients infected with COVID-19 [4, 8, 29].

Wang et al. presented noise-robust dice loss-based Pneumonia Lesion segmentation ensemble network (COPLE-Net) for segmentation of COVID affected areas [29]. COPLE-Net and noise-robust Dice loss are combined through ensembling network and exponential moving average of student model is used as teacher model which is updated adaptively by suppressing the student network to exponential moving average in case the student network has larger training loss. Li et al. presented COVID-19 detection neural network (COVNet) for COVID lesion segmentation from CT exams [15]. Unet and its variants are the most widely used encoder-decoder network for segmentation, since it capture high- and low-level features through encoder and semantic features through decoder. Chen et al. applied UNet+ + for the detection of COVID suspected lesion [5]. Hu et al. presented squeeze and excitation blocks to improve the representational of network by modeling the inter-dependencies between the channels of its convolutional features [13]. Similarly, Roy et al. fused spatial and channel SE blocks features by re-calibrating the feature representation channel-wise and spatially [25].

Multi-task deep learning has been applied for segmentation lung infection on CT images [7]. Infected lung areas are segmented initially, followed by segmentation of covid infected regions. The framework allowed the network to learn that features that can boast the segmentation performance. As multi- task mainly deals with the problem of small labeled dataset. The multi-task segmenter is trained using two-stream inputs to perform multi-class segmentation. It showed efficient performance for detection of infections. In another work, Louefki et al. presented efficient framework for robust segmentation and measurement of affected areas [19]. At first, region of interest (lungs) are segmented in CT images followed by segmentation of right and left lungs. After extensive image enhancement, authors applied modified local contrast enhancement for detail CT target. Experiments on COVID affected 275 CT scans plus data acquired from the EL-BAYANE center for radiology, and medical imaging showed significant improvement in detection performance. Structural relationships are critical for accurate detection of pulmonary lobes especially for COVID-19. Xie et al. presented relational non-local deep network by leveraging the structured relationships [31]. In order to produce self-attention weights, the framework learn both geometric and visual relationships among the convolution features. Initially, the model was trained on 5000 subjects from the COPDGene study, followed by retraining the network through transfer on 470 COVID-19 suspects.

Saeedizadeh et al. presented a variants (2D-anisotropic total-variation) of UNet-based framework for segmentation of ground-glass regions from CT images [26]. A regularization term is added in the loss function to promote the connectivity of the segmentation map for COVID-19 affected areas at pixel level. To deal with small dataset and reduce the number of training parameter, Capsules network has also been applied to solve the problem of CNN architecture [1, 12]. Afshar et al. applied capsule network for diagnosis of COVID patient in X-ray images [1]. Ma et al. presented a framework active contour regularized semi-supervised learning for segmentation of COVID infection on small labeled dataset [16]. Region-scalable fitting model is embedded into the loss function for active contour regularization and for refinement of pseudo labels of unlabeled data. Splitting method is designed to optimize the region-scalable fitting regularization and the segmentation loss. Xu et al. presented deep generative adversarial learning for weakly supervised COVID affected region segmentation [32]. The framework is optimized to segmentation of COVID affected areas though segmentator and replace the abnormal area with normal appearance by the generator. Zheng et al. multi-scale discriminative network by integrating channel attention block, pyramid convolution block and residual refinement block for segmentation of lungs area affected with COVID [33]. The pyramid convolution block uses different number of kernel with different size, hence, increases the receptive field, channel attention block fuses the both stages and focus features from segmented area only, and residual refinement block refine the feature maps, thus, integration results in strengthening the power to segment the COVID affected area of different sizes. Bizopoulos et al. combined Linknet, UNet, FPN, PSPNet with 25 randomly initialized and pretrained encoders (such as ResNet, DenseNet, ResNext, VGG, DPN, MobileNet, Xception,EfficientNet and Inception-v4) for lung segmentation and lesion segmentation and lesion segmentation [3]. Bř̈andle et al. presented large scale public lung ultrasound COVID-19 dataset [4] consisting of three classes (bacterial pneumonia, COVID19 and healthy). Deep convolutional neural network has been applied to classify the COVID-19 patient from ultrasound videos with high sensitivity. In addition to this, they have applied class activation maps for spatio-temporal local ization of pulmonary biomarkers.

3 The proposed depth-wise context attention network

In this section, we first describe the components of the proposed framework to automatically identify COVID affected regions from lungs CT images, followed by description of atrous and depth-wise. Figure 2, illustrates the proposed atrous convolution segmentation network. In earlier work, scaling up the ConvNets is widely explored and comparatively achieved better accuracy. However, most of the earlier work considers one of three dimensions, size, depth or width. Although it is possible to scale all dimensions arbitrarily, however it requires extensive efforts for tuning. Besides, it is challenging to achieve high performance. In this work, we consider the problem of scaling up the ConvNets and present a novel framework by balancing the scaling factors. We presented that a depth-wise multilevel concatenation is learning approach to combine different levels of features representation with improving the performance of the deep network and making generalization ability better. The network consists of multiple blocks that uniformly scale all dimensions (depth, width and resolution) and perform multilevel feature embedding. The compound depth, width and resolution scaling increase the receptive field and channels; thus, the network capture more fine-grained patterns. Unlike traditional CNN methods, the network arbitrarily scales the dimensions with a fixed set of scaling coefficients in each block followed by multilevel feature fusion by aggregating the high-level features to combine the contextual information. The inclusion of depth-wise components, squeeze-and-excitation results in better performance by capturing more receptive field than traditional convolutional layer; however, the parameters are almost the same.

The proposed model consist of encoder/decoder with skip connection, and bottom layer is shown in Fig. 2. We have further described each component of network in Figs. 3 and 4. Each encoder and decoder block consisted of proposed RSEDW (Residual-Squeeze-Excitation-Depth-wise) module. The bottom layer consisted of proposed 3D module and skip connections that cater the information from encoder block to decoder in order to reduce semantic

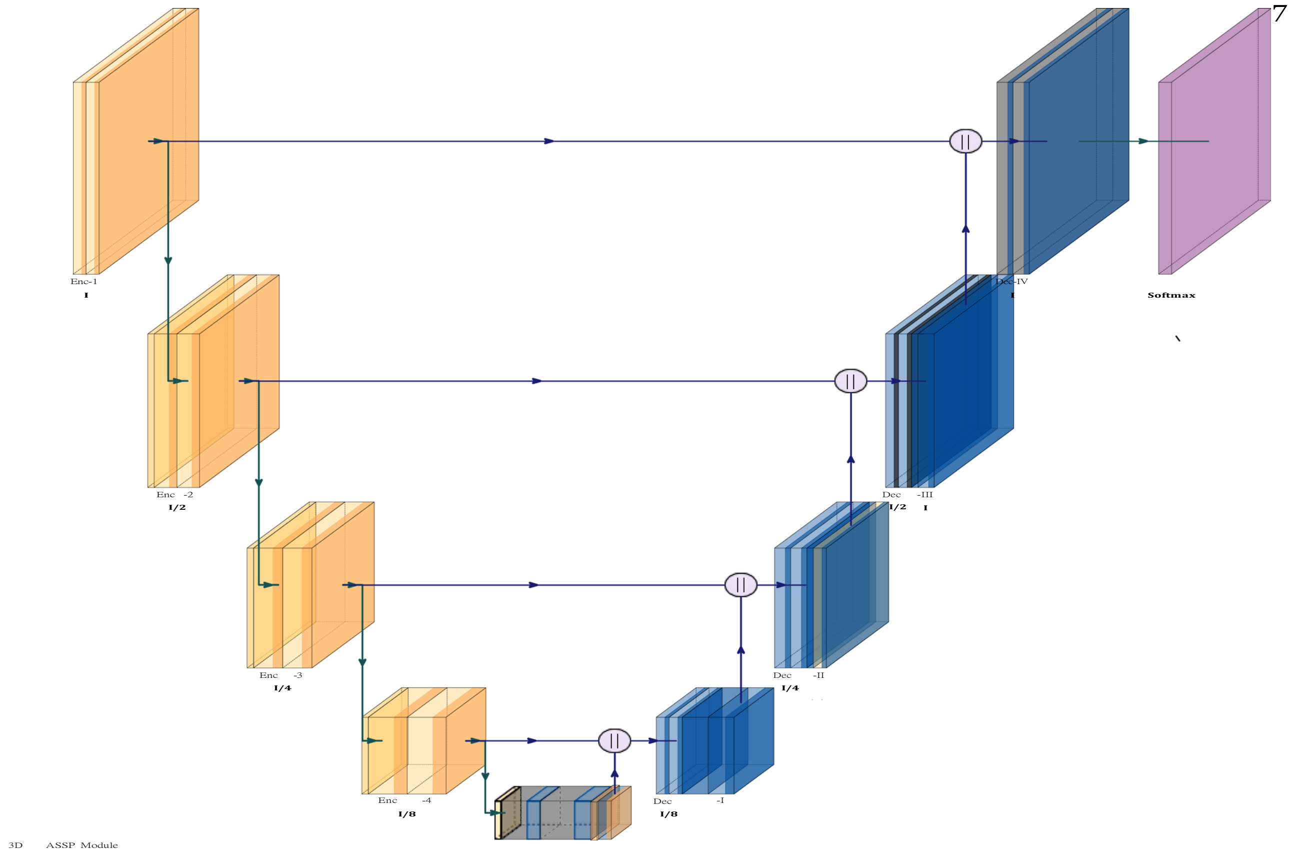


Fig. 2 Proposed depth-wise network with atrous convolution

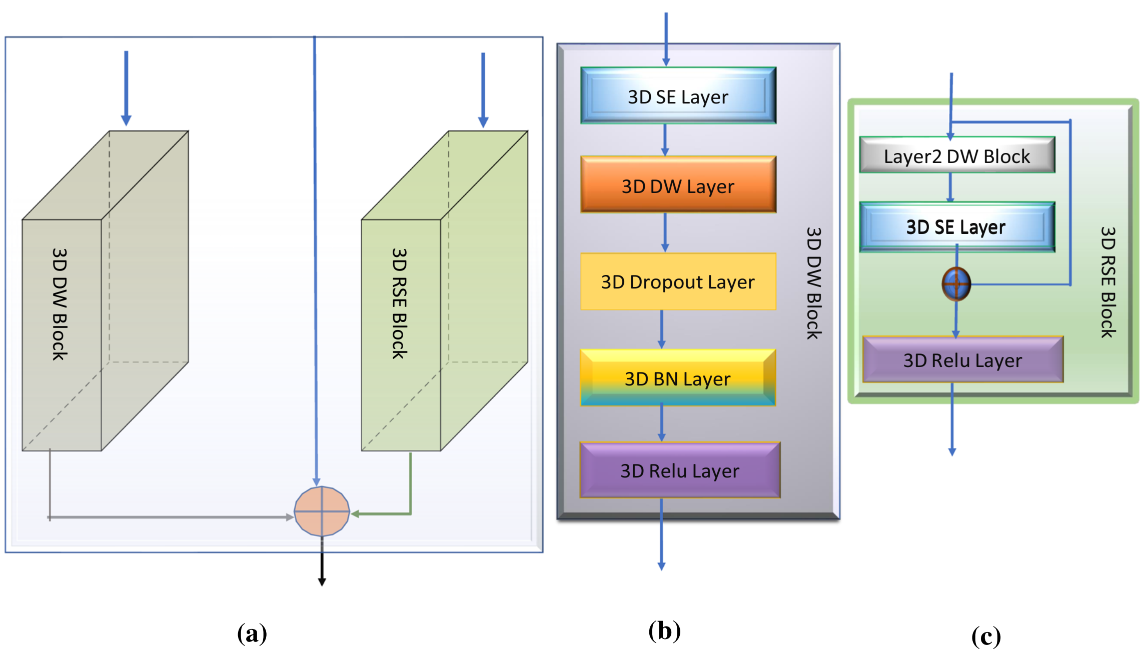


Fig. 3 Components of proposed framework **a** Encoder/Decoder block **b** 3D Depth-wise block **c** 3D residual squeeze and excitation block

gap in segmentation map. The feature maps are increased and 3D voxel dimension reduced from top to bottom in encoder side. 3D voxel dimension (height, width and depth) increases from bottom to top in decoder side with

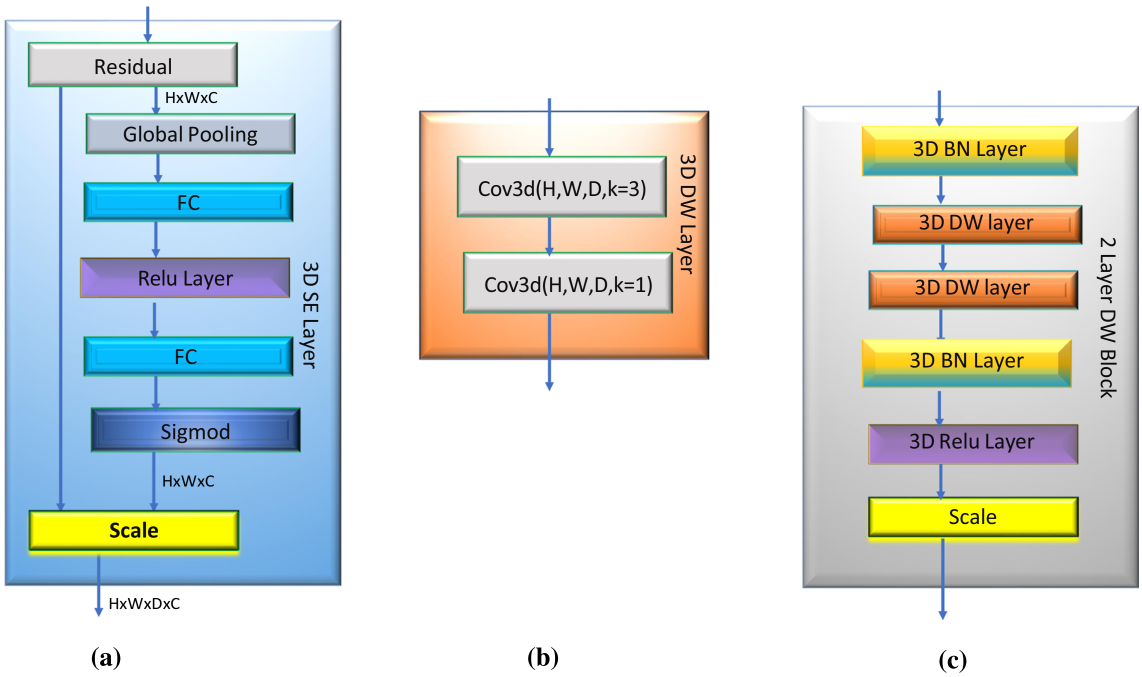


Fig. 4 Components of proposed framework **a** 3D squeeze and excitation layer **b** 3D depth-wise layer **c** 2 layer depth-wise block

decreased feature maps. We have used 3D Max-Pooling to reduce voxel dimension at encoder side and 3D Upsampling layer used to increase 3D voxel dimension at decoder side. As repeated combination of striding and max-pooling in consecutive layers captures the long range information in the deeper blocks, hence significantly impact the segmentation performance. As consecutive striding could be negatively impact the semantic segmentation of affected regions due to decimation of detail information. Atrous convolution mechanism allows the model to modify the field of view of filter adapitvely by changing the rate value. Besides, it also enable to the model to how densely to compute the features. Thus, we introduced atrous mechanism with different atrous rate as bottom layer for an accurate and efficient automated detection of COVID infection. The bottom layer comprised of proposed 3D ASPP (atrous spatial pyramid pooling) module that consisted of various blocks with different atrous rate (r = 1, 2, 3) is shown in Fig. 4. ASPP captures multi-scale information by effectively resampling the features at different scales for accurate and efficient classification of regions in an arbitrary scale and extract dense features without learning additional parameters. The 3D 1 $\times$ 1 Conv layer has been used at the end of decoder with softmax layer to get 3D segmentation map at output of proposed model. We have optimized our proposed module to get end to end better 3D segmentation map.

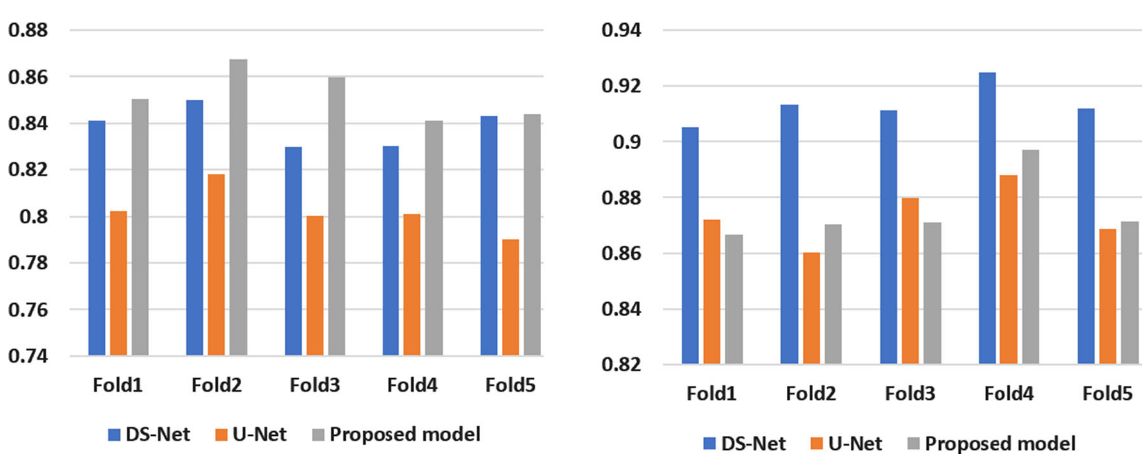


Fig. 5 Performance evaluation of proposed depth-wise network with with Atrous convolution with state-of-the-art networks

Table 1 Datasets distribution for training, validation and testing based on COVID19 and Non-COVID19

Datasets	Training cases	Validation cases	Testing cases	Cross-validation
COVID-19 dataset	12	4	4	10 fold
SegTHOR2019	24	8	8	10 fold

Table 2 HD of proposed and existing models on SegThor2019 dataset

Models	HD			
	Esophagus	Heart	Trachea	Aorta
VB-Net [9]	0.2590	**0.1272**	0.1453	0.1209
Mutlitask learning [11]	0.2743	0.1383	0.1824	0.1129
3D Multi-scale Network [30]	0.2883	0.1594	0.2045	0.1551
Residual UNet [28]	0.3310	0.2260	0.1930	0.2970
Two-stage Network [6]	0.4914	0.2417	0.2746	0.3081
U-Net [24]	0.2909	0.2534	0.2884	0.2984
DS-Net [10]	0.3129	0.1676	0.1945	0.2738
Proposed model	**0.2534**	0.1377	**0.1404**	**0.1168**

Best performing results are shown in bold

Table 3 Dice score of proposed and existing models on SegThor2019 dataset

Models	DSC			
	Esophagus	Heart	Trachea	Aorta
VB-Net [9]	0.8651	**0.9536**	0.9276	0.9464
Mutlitask learning [11]	0.8594	0.9500	0.9201	0.9484
3D Multi-scale Network [30]	0.8597	0.9459	0.9217	0.9433
Residual UNet [28]	0.8580	0.9410	0.9260	0.9380
Two-stage Network [6]	0.8166	0.9329	0.8910	0.9232
U-Net [24]	0.8384	0.9154	0.8872	0.9110
DS-Net DS-Net [10]	0.8512	0.9276	0.9003	0.9088
Proposed model	**0.8733**	0.9463	**0.9283**	**0.9533**

Best performing results are shown in bold

Table 4 Comparative evaluation of proposed framework on COVID19 dataset

Author and Year	Methods	Dataset	Overall dice score %
Ma et al. [17]	3D UNet	20 cases (Public)	80.33
Amyar et al. [2]	Multi-task deep learning	100 CT scans (Public)	88.00
Zhou et al. [34]	U-Net + FTL	100 CT scans and 9 CT volume(Public)	83.10
Adnan Saood et al. [27]	UNet + SegUNet	100 CT scans(Public)	74.10
Fan et al. [8]	Inf-Net	100 CT scans (public)	73.90
			82.00
Chen et al. [5]	U-net, M-A, M-R	100 CT scans (public)	85.00
			84.00
Proposed model	3D SERD model	20 cases (Public)	**88.08**

Best performing results are shown in bold

Figure 3a illustrate the core components of encoder/decoder block proposed depth-wise atrous convolution network. Each encoder/decoder consist of 3D Residual Sequeeze-Exitation Block and 3D Depth-Wise block with

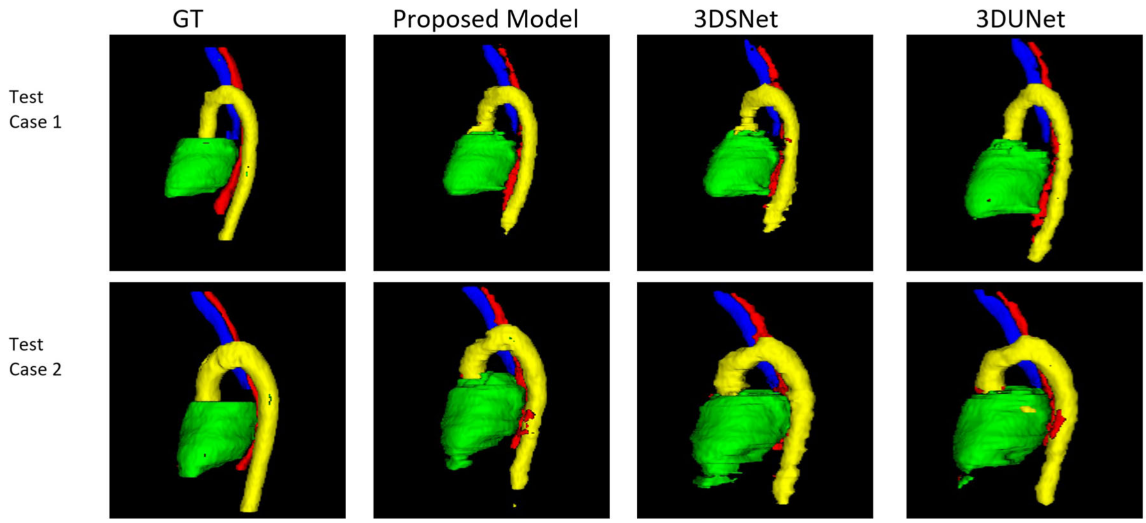


Fig. 6 Proposed Depth-Wise Multilevel Deep Network

skip connections. Figure 3b further illustrates the detail of 3D Depth-Wise block, and Fig. 3c describes the details of 3D Residual Sequeeze Excitation Block. The 3D depth-wise convolution layer consisted of conv3d with filter size 3, and conv3d with filter size 1 is shown in Fig. 3b. This layer is used as a building block for other proposed models. The proposed 3D DW(depth-wise) block consisted of 3D SE(squeeze and excitation)-layer, 3D DW-layer and other 3D regularization layers such as 3D BN (batch-normalization) layer, ReLU and 3D dropout layer are shown in Fig. 3b. Figure 3c illustrates the detail of 3D Residual Sequeeze Excitation Block which consist of 3D SE block in concatenated with 2 Layer DW block and residual connection with ReLU activation function. The 2 Layer DW block consisted of 3D batch-normalization, two cascaded 3D depth-wise convolutional layers and regularization layers such as 3D dropout, 3D Norm and ReLU is shown in Fig. 4c.

4 Results and discussion

In this section, we presented experimental setup and evaluation of proposed depth-wise multilevel concatenated deep neural network. To generalize the performance, we have performed 10 fold validation on benchmark 5-class COVID-19 CT image datasets (COVID-19 dataset and SegTHOR2019). The COVID-19 segmentation dataset consists 20 CT scans of patients and their respective annotated masks of the right lung, left lung and COVID19 lesions [35]. The dataset consists of 20 CT scans of patients and their respective annotated masks. The masks were created by junior annotators and were refined by senior radiologists having 5 years' experience. Finally, radiologists having 10 years' experience verified these annotations. On average, as CT scans have a good spatial resolution (250 slices), 400 min for delineatiung one CT scan volume were required. The test sample based on COVID-19 is shown in Fig. 1. We have also used SegTHOR2019 dataset consists 40 CT scans of patients and their respective annotated masks. The proposed model was implemented using the Python-based PyTorch framework. The proposed model was trained using Adam optimizer for optimization at a learning rate of 0.0001. Batch size 4 was used for training the proposed 3D model, and the number of epochs was set to 200 for all datasets. The training was performed using the NVIDIA 12 GB GPU memory-based memory machine equipped with single GPUs. The training required 12 h (Fig. 5).

Experimental results showed that propose framework achieved considerably improvement in diagnostic performance of affected area in comparison to state of the methods. The proposed 3D model-based COVID19 segmentation Dice similarity coefficients (DSC) score for individual and average of all classes (left, right and covid19 infection) with state-of-the-art models is shown in Table 1. The proposed model produced better Dice score as compared to existing state-of- the-art models as shown in Table 1. Similarly, the Hausdorff distance (HD) has been computed for all classes and compared the performance of proposed model with existing state-of-the-art models is shown in Table 2. The dataset has been divided into 80% for training and 20% for testing. We have used 5 fold cross-validation approach for further judge model validation and generalization. In order to check generalization capability, the proposed model has been trained and tested on SegThor2019 dataset. The DSC and HD has been calculated for SegThor2019 dataset using proposed and

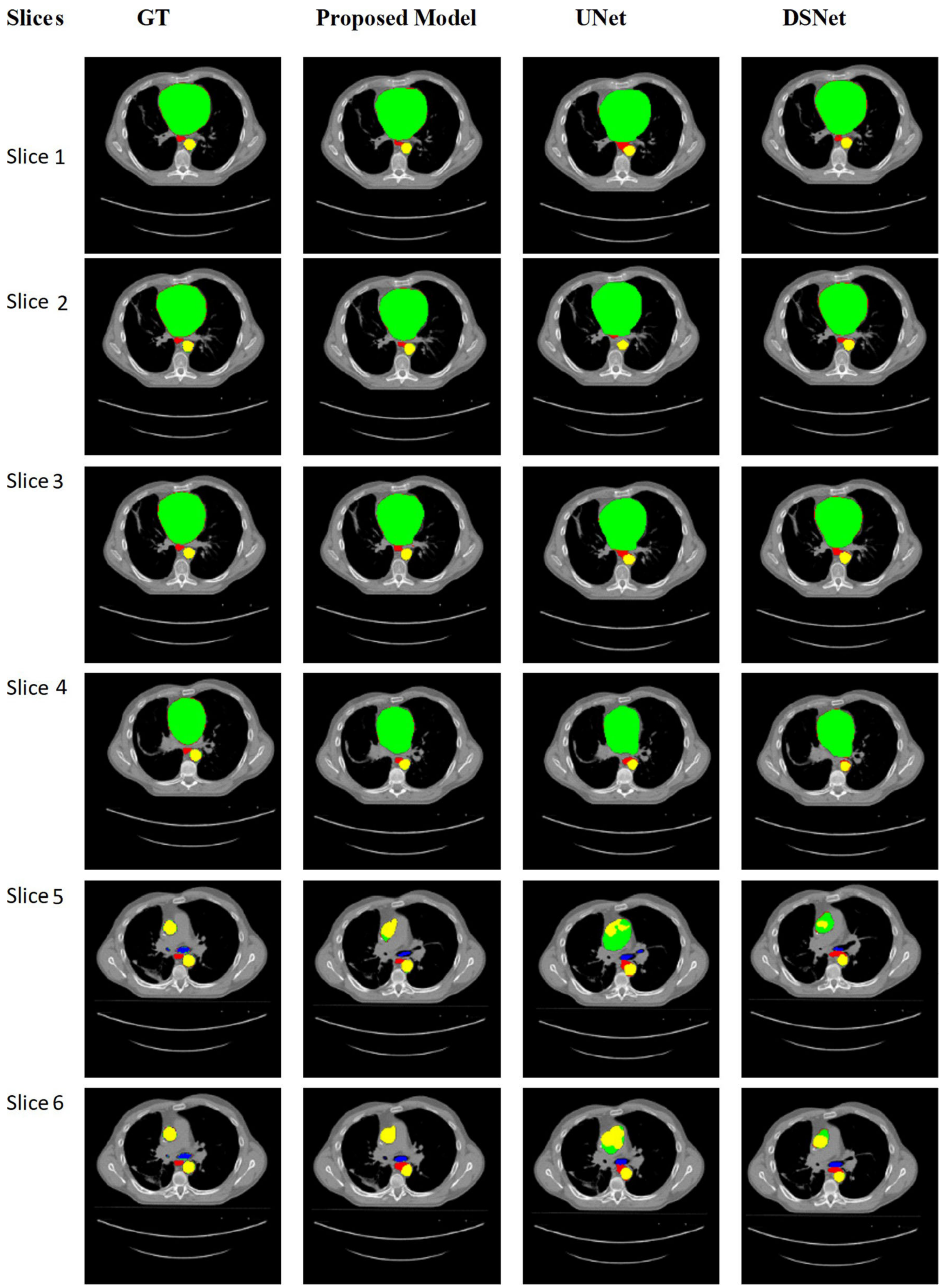


Fig. 7 Comparison of Proposed Depth-Wise Multilevel Deep Network with state-of-the-art network

existing deep learning models. The results are shown in Tables 3 and 4. The proposed model also produced excellent score on both dataset.

A comparative visualization of for proposed and existing models with different number of slices of a single case has been shown in Figs. 6 and 8. We can observe that

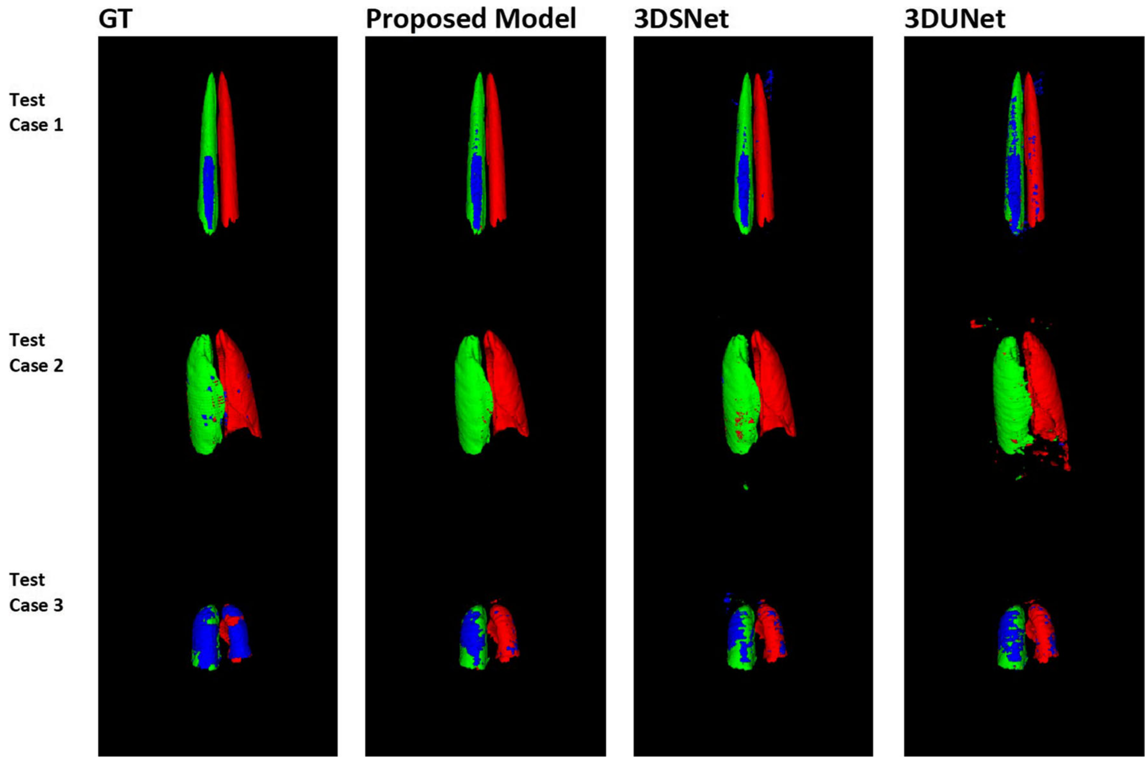


Fig. 8 Segmentation results Proposed Depth-Wise Multilevel Deep Network vs State-of-the-art methods

proposed approach segmented more true positive values for infection disease as shown in blue color as compared to existing models. The 3D visualization of three different cases is shown in Fig. 7. The best, average and worst case has been provided based on proposed and existing models. The first row shows that proposed model produced less false positive as compared to 3DDS-Net and U-Net. Similarly, in second row, 3DU-Net produced more false positive as shown in second row and last column. The third row demonstrated the worst case, where proposed model again achieved good true positive rate as compared to existing models (Fig. 8).

4.1 Discussion

We presented depth-wise multilevel features concatenated deep neural network for the diagnosis of COVID affected areas from lungs CT images. We consider the problem of scaling up the ConvNets and present a novel framework by balancing the scaling factors. The depth-wise multilevel concatenation is learning approach is presented with the goal to combine different level of features representation to improve the performance of the deep network and to make generalization ability better. The network consists of multiple blocks that uniformly scales all dimensions (depth, width and resolution). We deployed a parallel structure with different atrous rate to capture different receptive fields in different scale is shown in Fig. 4. By experiment sitting, in our proposed model, the atrous rate(r = 1, 2, 3) for different atrous 3D blocks produced optimal performance (Figs. 9, 10 and 11).

To evaluate the performance of proposed framework, we have compared the performance of proposed framework with state-of-the-art methods such as multi-resolution VB-nets [9], multi-task learning with label dependencies [11], 3D Multi-scale Network [30], Two-Stage Network [6], Residual UNet [28], U-Net [24], DS-Net [10], Few shot learning [17], multi-task learning [2], Inf-Net [8], UNet + SegUNet [27]. Table 3 describes the comparative evaluation of dice score of proposed framework with state-of-the-art methods on SegThor2019 dataset, and Table 2 describes comparison of HD score of proposed with state-of-the-art methods. Results showed that proposed framework achieved significant gain in dice and HD score 87.33% and 25.34%, respectively. Similar behavior can be noticed for COVID19 dataset. The promising and encouraging results of proposed framework in diagnosis of COVID-19 effected areas from radiography images indicate that it can be used as an application for detection of COVID. The promising and encouraging results of proposed depth-wise framework in detection of COVID affected patient from X-rays images indicate that deep learning has a greater role to play in fighting against COVID-19. Further in-depth analysis can be performed,

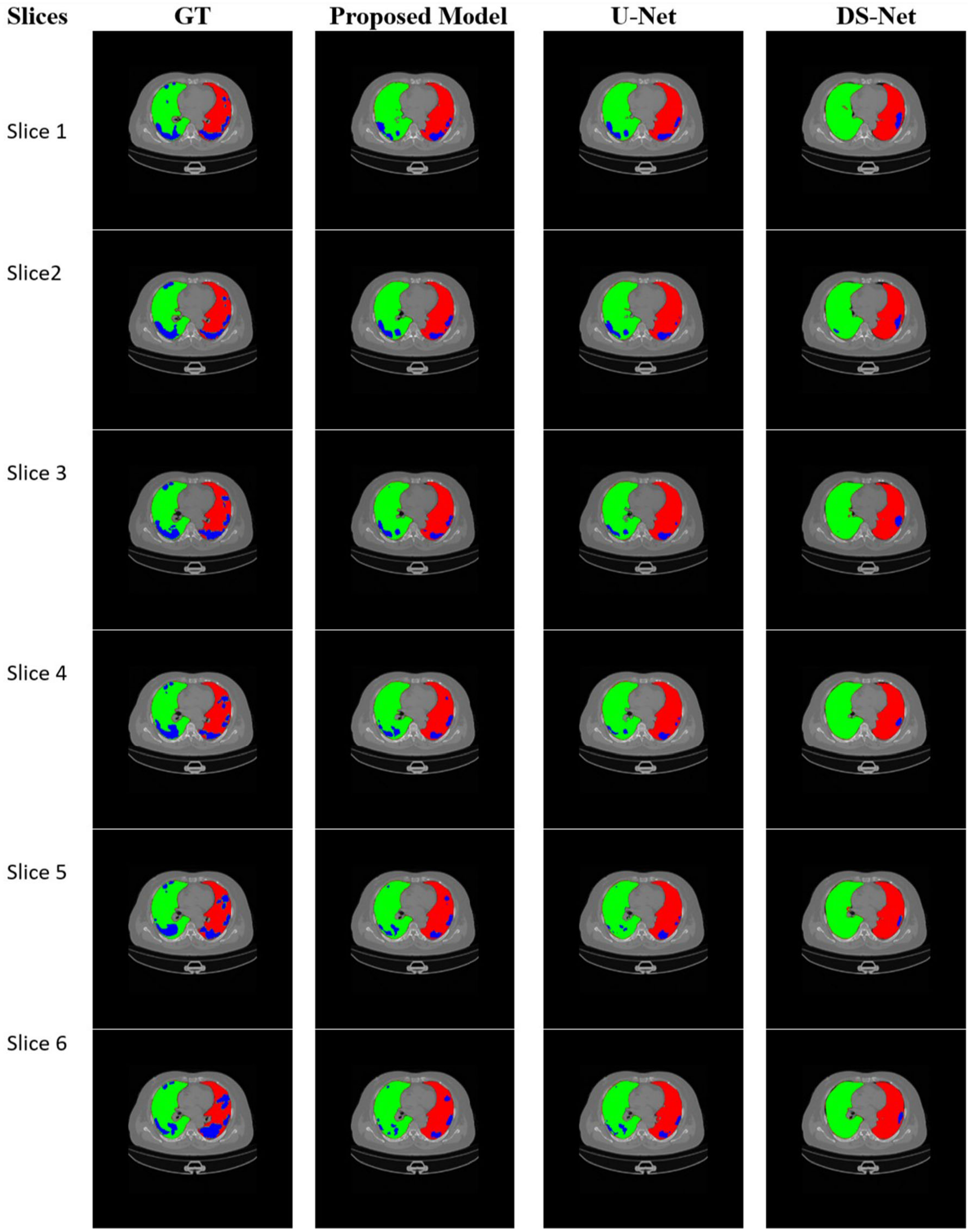
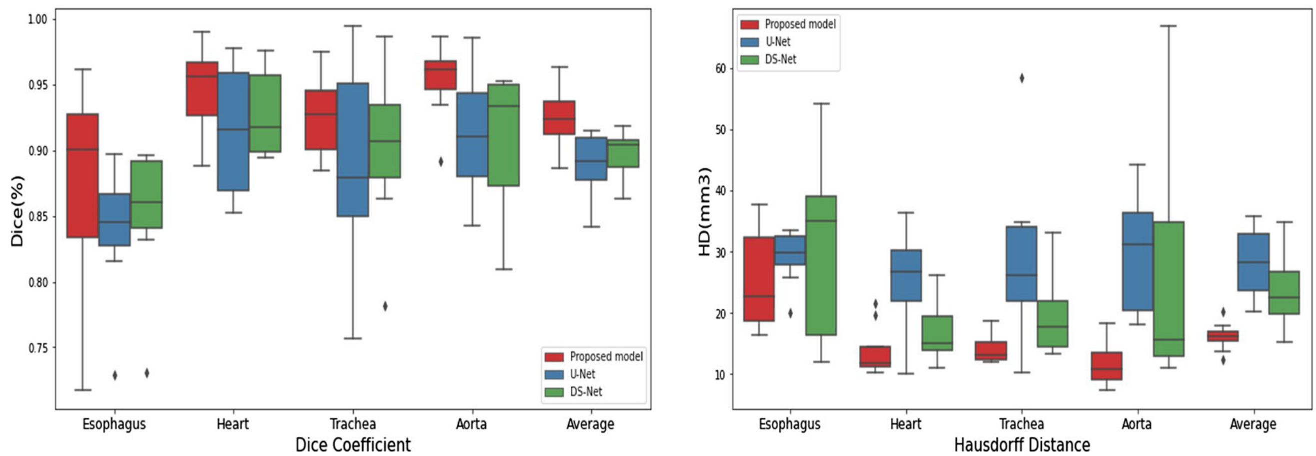


Fig. 9 Slice-wise visualization of test case based on proposed and existing state-of-the-art models. The green color represents left lung, red color represents right lung, and blue color represents covid-19 infection disease

and large data can be used to improve the detection performance.

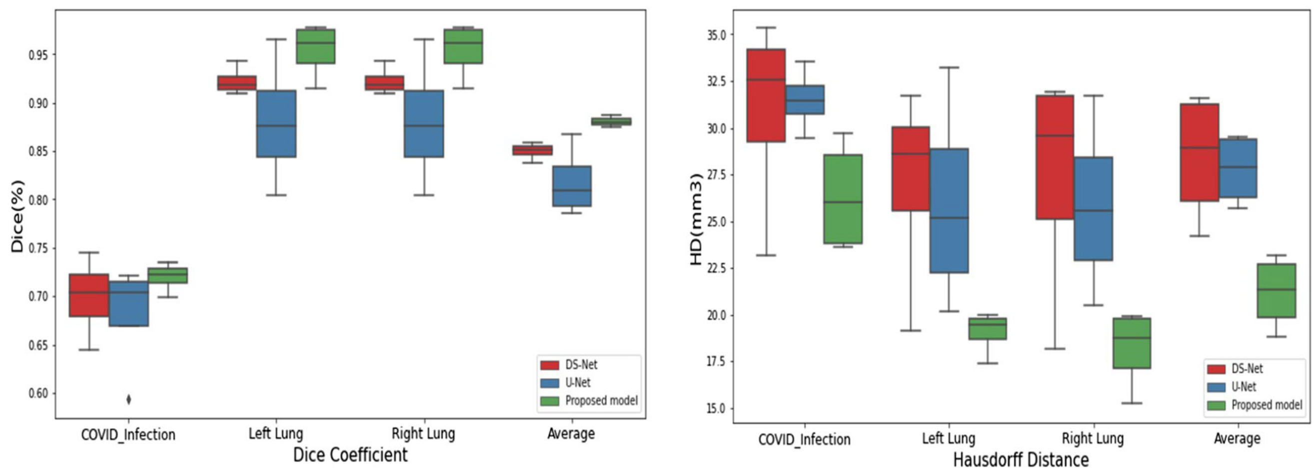
5 Conclusion

The exponential increase in COVID-19 patients is overwhelming healthcare systems across the world. With limited testing kits, it is impossible for every patient with



(a) DSC for SegThor2019 **(b)** HD for SegThor2019

Fig. 10 Comparative evaluation of proposed network convolution on SegThor2019 dataset



(a) DSC for COVID-19 **(b)** HD for COVID-19

Fig. 11 Comparative evaluation of proposed network on COVID19 dataset

respiratory illness to be tested using conventional techniques. In this paper, we presented a novel framework for classification of COVID effected areas. We presented depth-wise deep neural network that encode multi-scale depth-wise information. Besides, we introduce a novel multilevel depth deep framework and atrous mechanism with different atrous rate as bottom layer for an accurate and efficient automated detection of COVID infection. Considering depth-wise component along with squeeze-and-excitation results in better performance by capturing more receptive field as compared to traditional convolutional layer however, the parameters are almost same. The extensive experiments on benchmark CT dataset demonstrated the effectiveness of proposed framework by achieving dice 0.8733 and 0.8808 for SegThor2019 dataset and COVID19 dataset using in comparison to cutting-edge methods especially based on transfer learning.

Declarations

Conflict of interest Authors declare no conflict of interest.

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