Deep Learning Approaches for Optimized Segmentation in COVID19 CT Images

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***Abstract*— Modern healthcare relies heavily on medical image analysis. The task of analyzing and diagnosing based solely on images is challenging, which has led to the implementation of computer-aided diagnosis techniques. RT–PCR, a screening tool, has lower sensitivity in the diagnosis of COVID-19, and medical imaging methods such as computed tomography (CT) offer significant benefits over other methods. Segmentation is the most challenging issue when working on medical images, as the deep learning approach has recently become commonly used in diagnosis. A convolutional neural network (CNN) framework called U-Net was created for image processing's semantic pixel segmentation. This paper focuses on assisting radiologists in providing a more detailed depiction of COVID-19 infection on CT images, including various infection categories and lung conditions. In this study, we conducted an experiment on preprocessing for better segmentation results via the U-Net model. Patchwise segmentation yields better results than linear and cubic interpolation does.**

Keywords— radiology, pneumonia, CNN, PCA, GLRLM)

I. Introduction (*CORONAVIRUS COVID-19*)

Recently, a pandemic caused by the novel coronavirus (COVID-19) severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has spread throughout the world. One of the diseases that has been shown to be among the most harmful and poses a serious threat to human civilization is COVID-19. A significant portion of the global population has been quarantined due to the COVID-19 pandemic, which has also devastated several industrial sectors and sparked a global financial crisis. The clinical features of early-stage COVID-19 include respiratory symptoms, fever, cough, dyspnea, pneumonia, and lethargy. In severe situations, COVID-19 can lead to multiple organ failure or acute respiratory distress. It also affects the pulmonary and circulatory systems. As a result, COVID-19 infection is a significant healthcare concern and a global hazard. On January 30, 2020, the World Health Organization (WHO) deemed the outbreak a public health emergency of global concern. To confirm the prevalence of COVID-19, reverse-transcription polymerase chain reaction (RT–PCR) is typically employed. Unfortunately, there are currently no clinical vaccinations or exact drugs or treatments that can be used to address this contagious disease effectively. Compared with RT–PCR, chest X-rays are inexpensive, quick, and generally accessible for the early diagnosis and screening of COVID-19. It is affordable and can be made available in the majority of healthcare settings, even in developing nations. Certain pulmonary symptoms associated with COVID-19 can be identified with the help of this noninvasive imaging technology. Indeed, symptomatic patients find it particularly helpful (and practical). The requirement for skilled radiologists to interpret radiography images is one of the system's constraints. As a result, computer-aided diagnostic systems (CAD) can aid radiologists in precisely and quickly identifying COVID-19 cases.

A. Diagnosis of COVID-19 from CT Images

Alveoli are harmed by COVID-19 directly, which affects the lungs (tiny air sacs). The purpose of the alveolus is to supply blood vessels with oxygen. Red blood cells receive their oxygen from these blood veins or capillaries (red blood cells). Ultimately, red blood cells (RBCs) supply oxygen to every single organ in the body. Additionally, the inability of internal organs to operate properly due to a lack of oxygen causes a deficiency in the body. The inclusion criteria for the diagnosis of COVID-19 included the following: 1. Pharyngeal swabs tested positive for SARS-CoV-2 by RT–PCR. 2. Individuals admitted for isolation or therapy. 3. The C-reactive protein level in the blood test may indicate COVID-19 risk. 4. A thin-section CT scan of the chest that reveals any pneumonia symptoms.

Serial CT examinations may be beneficial for tracking the progression of the disease and ensuring prompt therapy because COVID-19 patients exhibit recognizable CT characteristics during the course of the disease. Patchy ground glass opacities (GGOs), with a predominantly peripheral distribution under the pleura and along the bronchovascular bundles, are a distinguishing feature of COVID-19. These GGOs may merge into dense, consolidative lesions. The number of lesions may increase quickly as the disease worsens and spreads to central regions, more frequently affecting the left lower lobe than the right upper/middle and right lobes. The following characteristics of the CT findings were examined: location, distribution, size, and type. Locations of the various lobes and involved segments. The lung's outer third was described as peripheral, the interior two-thirds as central, or both as peripheral and central. The lung pulmonary window had dimensions of 1500 Hounsfield units (HUs) in breadth and -700 HU in level.

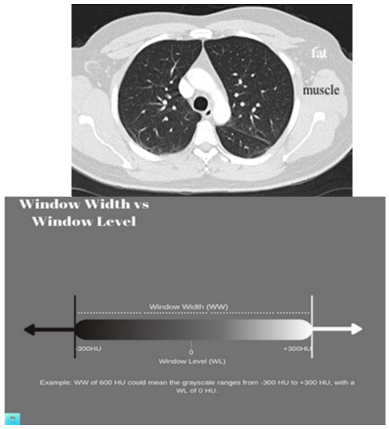


Fig. 1.1 Window width vs. window level

The CT grading approach suggested by Camiciottoli was used to determine the severity of pulmonary fibrosis. There were two components to the scoring system: one for the type of lesion and the other for the extent of the lesions. The maximum score was 30. Groundglass opacities, linear opacities, interlobular septal thickening, reticulation, honeycombing, and bronchiectasis were the different types of lesions, and they were given scores of 1, 2, 3, 4, and 5, respectively. Whether a lesion type was identified in 1, 3, 4, 9, or more than 9 lung segments—which were rated as 1, 2, and 3, respectively—determined how extensive it was. India categorizes the severity score into three categories: mild (score < 7), moderate (score 7 to 18), and severe (score >18).

II. RELATED WORK

Using machine learning algorithms and signal/image processing techniques, COVID-19 can be automatically diagnosed from CXI and CCTI. Numerous models for the use of CXI and CCTI in the diagnosis of COVID-19 have been proposed by researchers worldwide.

Narinder Singh Punn et al. [1] proposed that to effectively encode and decode semantic and varying resolution information, the COVID-19 hierarchical segmentation network (CHS-Net) uses two cascaded residual attention inception U-Net (RAIU-Net) models. These models include a residual inception U-Net model with a spectral spatial and depth attention network (SSD), which is developed with contraction and expansion phases of depthwise separable convolutions and hybrid pooling (max and spectral pooling). Shuo Wang et al. [2] used the entire lung's three-dimensional bounding box as the ROI rather than just using lung fields that have been segmented or lesions. The performance of the DL system for prognostic analysis, DenseNet121-FPN for lung segmentation in chest CT images, and the suggested novel COVID-19Net for COVID-19 diagnosis was assessed via Kaplan–Meier analysis and the log-rank test. Hemanta Kumar Bhuyan et al. [3] proposed OLO-based deep learning to find several contaminated area locations. Three different types of images—pixel-level, CORONAL, and SAGITTAL images—are tested. Each image's diseased area is located via statistical measurement. A deep convolutional neural network (CNN) is employed for mass segmentation of the diseased zone to identify and classify the specific contaminated area. Yazan Qiblaweya et al. [4] proposed DenseNet 121 as the best-performing network for lung segmentation with IoU and DSC, and DenseNet201 FPN achieved the best lesion segmentation performance with IoU and DSC. M. Turkoglu [5] proposed the multiple kernels-ELM-based deep neural network (MKs-ELM-DNN) method for the detection of novel coronavirus disease, in which features are extracted from CT scan images via a pretrained CNN-based DenseNet201 architecture. Vruddhi Shah et al. [6] performed time analysis with a self-developed model named CTnet-10, which was designed for COVID-19 diagnosis, and the time taken by the CTnet-10 model to predict the results was only 12.33 ms. Andrea Loddo et al. [7] compared different architectures on a public and extended reference dataset, and the most suitable architecture was VGG19, which achieved 98.87% accuracy and achieved 95.91% accuracy in patient status classification. Athanasios Voulodimos et al. [8] proposed a deep learning semantic segmentation approach for the annotation of symptomatic lung areas for COVID-19 patients via a fully CNN. Mohammad Rahimzadeh et al. [9] used the Grad-CAM algorithm to visualize the extracted features of the network to determine the areas of infection and utilized ResNet50V2, a modified feature pyramid network, and the designed classification layers to achieve the best results. Zhiliang Zhang et al. [10] proposed a ResAU-Net based on the U-Net network structure for the segmentation of the infected area. An attention mechanism was added to improve the network's attention, and subpixel convolution was used to achieve the upsampling of the feature image. Ramin et al. [11] proposed a two-route convolutional neural network (CNN) by extracting global and local features for detecting and classifying COVID-19 infection from CT images and used two different strategies, fuzzy c-means clustering and local directional pattern (LDN) encoding methods, to represent the input image differently. R. Prabha et al. [12] proposed hybrid swarm intelligence and fuzzy discrete particle swarm optimization (DPSO) algorithms for preprocessing images. Dropout CNN classification was applied to detect lung abnormalities, and a Lee filter with equalization was utilized to enhance the pictures to reduce noise. The CLAHE algorithm was used to improve the lung picture. Pramod Gaur et al. [13] used the concept of empirical wavelet transformation for preprocessing, the empirical wavelet transform (EWT) for feature extraction, and the deep learning technique DensNet to obtain classification from extracted information. Pradeep Kumar Chaudhary et al. [14] introduced the Fourier-Bessel series expansion-based decomposition (FBSED) method to decompose CXI and CCTI into subband images (SBIs), ImageNet challenges are used for feature extraction, and CLAHE performs histogram equalization on each tile of an input image. Pramod Gaur et al. [15] used stochastic gradient descent (SGD) to minimize the sum of squared residuals. The Adam optimizer keeps an average of past squared gradients and is stored in the variable, and DenseNet 169 tends to yield the best results.

Navid Hasanzadeh et al. [16] developed and evaluated four artificial intelligence (AI)-based lesion segmentation and quantification methods from chest CT images via the U-Net, attention U-Net, R2U-Net, and attention R2U-Net models. Danial Sharifrazi et al. [17] proposed a CNN-SVM model with a Sobel filter (CNN-SVM + Sobel), and the classification operation was accomplished by FC layers via two methods: (i) sigmoid and (ii) SVM.

Maria V et al. [18] proposed two methods for noise reduction in CT images: 3D extension of fast rank algorithms (Rank-2.5D) and 3D extension of a nonlocal means algorithm (NLM-2.5D). Mehdi Yousefzadeh et al. [19] extracted the PDF to grade the infection of each lobe, selected five specific thresholds as feature vectors, assigned this feature vector to a support vector machine (SVM) model, and calculated the p value at different pixel thresholds via t test statistics. Aswathy A.L. et al. [20] used principal component analysis (PCA) for dimensionality reduction, a scaled conjugate gradient backpropagation neural network to detect severity, and a pretrained model, ResNet-50, for COVID-19 detection and feature extraction via ResNet-50 and DenseNet-201 to estimate the severity of patients. Shou-Ming Hou et al. [21] proposed a fusion algorithm in which histogram equalization is used, which results in maximum entropy of the image, thereby improving the clarity of the weak edge. The median filter, K-means algorithm, and mathematical morphology are added to the Canny algorithm, which can make the edge of the inspected more accurate. The OTSU algorithm is used to automatically obtain the best threshold.

The segmentation of diagnostic images is highly needed because it can be used for a multitude of medical research purposes. For the best identification of regions of interest and quick segmentation, designing an efficient segmentation technique based on deep learning algorithms is critical.

Preprocessing is the most important type of image processing. The image needs to be resized for medical diagnosis. We initially used linear and cubic interpolation in preprocessing. Cubic interpolation is better than linear interpolation. However, more pixel loss occurs while the image is resized via both methods. Therefore, we propose a method in which instead of resizing, we create patches of images and then train the model with every patch and predict its mask. After predicting the mask of each patch, we reconstructed the image and binarized the mask with a 0.5 threshold.

III. Prospective Methods

The process is based on the MIScnn [22] (Medical Image Segmentation with Convolution Neural Networks) model, which uses extensive data augmentation, preprocessing, and batch creation for straightforward training and evaluation of medical image segmentation. The implemented image segmentation pipeline for COVID-19 is shown in Fig. 2, and the steps are summarized as follows:

1.Dataset consisting of COVID-19 CT images (.nii.gz format)
2.Data augmentation and different preprocessing techniques.
3.Implementation of the standard U-Net model
4.Model prediction
5.Evaluation Techniques (e.g., F1 score, Dice coefficient)

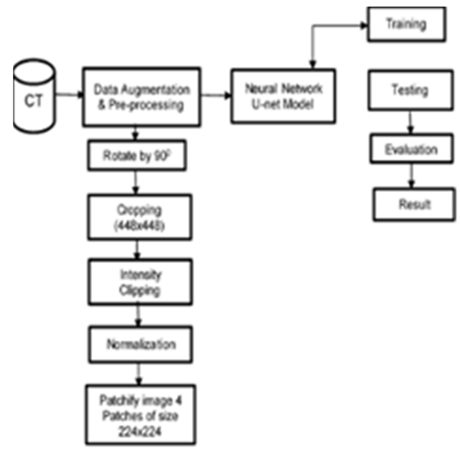


Fig. 2.1 Block diagram of the implemented segmentation of COVID-19 CT images.

A. Dataset

CT scans play a supportive role in the diagnosis of COVID-19 and are a key procedure for determining disease severity. The dataset is publicly available and consists of 20 CT scans of patients diagnosed with COVID-19 as well as segmentations of the lungs and infections made by experts. We prepared the dataset by performing two tasks: first, we created a CSv file containing paths of all nii files from the original dataset; second, we unpacked the volume data and stored the CT slices and mask slices from the corresponding volume data. While storing the slices, only the middle 60% of the slices from the volume are considered. The number of slices available is 2112.

B. Data Augmentation

The primary goal of data augmentation is generally to prevent overfitting, thereby enhancing the performance of the model. The dataset has CT scans of 20 patients with multiple slices of each patient. A total of 2112 slices of the CT scan, lung mask and infection mask are available, each with a size of 512x512. Two augmentation techniques are used: rotation, in which all the images are rotated by 900; and the crop technique, where images are cropped to a size of 448x448.

C. Preprocessing

The dataset was divided into subsets with 80% for training and 20% for validation. Then, a preprocessing pipeline that was applied to each of the subsets separately was created. Many preprocessing techniques are applied to data for pattern identification and to avoid overfitting. It is necessary to standardize the images to Hounsfield units (HUs), which are grayscales widely used in the radiography field, to ensure the accomplishment of the dynamic intensity of the signal. Therefore, to achieve this, data scaling and normalization are highly important. We perform intensity clipping of images in the range of -1000 to 400 HU. Then, the images are normalized to the min–max scaler [0, 1] or [-1, 1] scale. All these preprocessing techniques are applied to all the lung masks. We performed 4 patches of each image of size 224x224 and assigned them to the neural network U-Net model.

IV. NEURAL NETWORK ARCHITECTURE

Choosing a precise neural network is a crucial factor in image segmentation. There is a broad spectrum of neural network architectures, each characterized by its own set of strengths and weaknesses. The characterization of methods is based on TensorFlow through the Keras open-source neural network library, which provides a user-friendly interface encompassing widely implemented key components of the neural network. To prevent an excessive increase in parameters and avoid complex convolution, a standard U-Net architecture is employed. U-net is a semantic segmentation technique that was originally proposed for medical image segmentation.

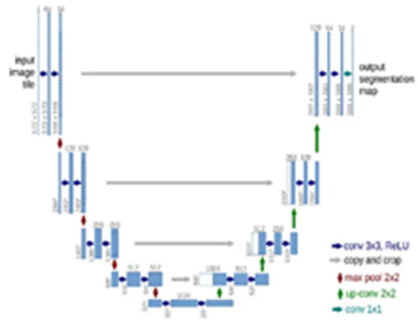


Fig. 4.1 U-Net architecture

A. U-Net Architecture

The U-Net architecture was proposed by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015. The U-Net architecture is named after its distinctive U-shaped design. It consists of an encoder path and a decoder path connected by "skip connections," which makes it a fully convolutional network. A step-by-step explanation of the U-Net model is as follows:

1. Encoder Path: The encoder path is similar to a standard convolutional neural network (CNN). It consists of multiple layers of convolutional and pooling operations. These layers are responsible for extracting features from the input image and gradually reducing its spatial dimensions.

2. Downsampling: In the encoder path, the spatial dimensions are typically reduced by pooling operations (e.g., max pooling). Downsampling helps in enlarging the receptive field and capturing more contextual information.

3. Decoder path: The decoder path is the counterpart of the encoder path. It involves upsampling the feature maps to gradually restore the original spatial dimensions. Upsampling is typically performed via transposed convolutions (also known as deconvolutions).

4. Upsampling and skip connections: The critical innovation of the U-Net architecture is the use of skip connections. These connections are designed to transfer feature maps from the encoder path to the corresponding decoder path at the same resolution. By doing so, U-Net can combine low-level and high-level features, which is beneficial for precise segmentation.

5. Upsampling and Concatenation: In the decoder path, the feature maps are upsampled and then concatenated with the corresponding feature maps from the encoder path through the skip connections. This concatenation helps in preserving spatial information and fine-grained details from the earlier layers.

6. Final Layer: The final layer of the U-Net is a 1x1 convolutional layer with a sigmoid activation function. This layer performs pixelwise classification, generating a segmentation mask where each pixel represents the probability of belonging to a particular class or object.

B. Evaluation

To assess the consistency of segmentation models, various metrics are generally used, such as the Dice coefficient, IOU, recall, and precision.

1. Precision: A ratio of correctly predicted COVID-19 divided by the total number of pixels that are positively predicted as COVID-19.

$$Precision = \frac{TP}{TP + FP}$$

TP is a true positive, i.e., positive cases are appropriately categorized, and FP is a false positive where cases are wrongly classified.

2. Recall: A ratio of correctly classified instances divided by actual instances present.

$$Recall = \frac{TP}{TP + FN}$$

where FN represents false negatives, which are positive instances wrongly classified as negative.

3. Dice Coefficient: To evaluate the relationship between the predicted result and ground truth, the Dice coefficient, also known as the Dice score or DSC, is used in segmentation.

$$Dice = \frac{2|A \cap B|}{|A| + |B|}$$

where A & B are the predicted result and ground truth, respectively.

4. Intersection over Union: The IOU is used to calculate the relationship between the predicted result and the ground truth. It is a ratio of the predicted outcome and the associated labels between the size of the intersection and the size of the union.

$$IoU(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

where A is the predicted result and B is the ground truth. It generally ranges between 0 and 1. If both A&B are empty, then it results in 1. toolbar.

V EXPERIMENT AND RESULTS

The dataset used in the following experiment was obtained from Kaggle in the NII/Nifty format type. We conducted experiments with different image sizes and interpolations.

The dataset is arranged as shown in Fig.

Fig. 5.1 Data structure

The dataset was divided into subsets with 80% for training and 20% for validation.

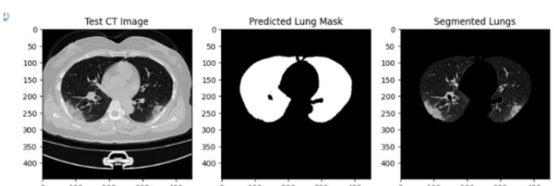
Parameters and environment

In the model training process, the following configuration parameters are used:

1. Optimizer = Adam
2. Loss = dice loss
3. Batch size = 32
4. Epoch = 100
5. Learning rate = 0.0001

Segmentation Results:

The results of lung segmentation are shown in Fig. 1.



VI CONCLUSION

In this work, several common approaches to image segmentation applied to chest computed tomography images for the detection of pulmonary nodules were presented. It was evaluated with the deep learning approach U-Net with different configurations of architectures, parameters and data augmentation distributions. In this study, we conducted an experiment on preprocessing for better segmentation results via the U-Net model. Patchwise segmentation yields better results than linear and cubic interpolation does. The results show that the IoU with cubic interpolation is better than that with linear interpolation. Patchwise segmentation yields good results for all the evaluation metrics, with an IoU of 0.98, Dice coefficient of 0.97, F1 score of 0.98, precision of 0.97 and recall of 0.98, compared with interpolation. Instead of resizing the images, when patches are given to the training model, a better result is obtained.

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