Automatic detection of infected areas of CT images in COVID-19 patients using Inf-Seg-Net

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Abstract
The swift spread of the coronavirus disease (COVID-19) makes it extremely difficult for early detection and diagnosis of the virus, necessitating timely care. Numerous research institutes, laboratories, diagnostic facilities, non-governmental organizations, and government-funded organizations collaborate daily to identify challenges that arise throughout the COVID-19 virus detection procedure. The first screening method utilized to locate COVID-19 was reverse transcription polymerase chain reaction (RT-PCR). However, advancements in technology have paved the way for the use of computed tomography (CT) imaging in early screening. Radiologists and research scientists are now exploring the potential of artificial intelligence (AI) and deep learning (DL) techniques to develop an automated disease detection model utilizing CT images for screening purposes. The aim of this research is to simplify infection segmentation by using Inf-Seg-Net, a network-based technique with dense UNets and residual blocks for infection classification. The proposed framework involves three stages: preprocessing CT images using contrast limited adaptive histogram equalization based on non-local mean filter (CLAHEN), followed by logarithmic non-maxima suppression (LNMS) for lung segmentation, and an infection segmentation network (Inf-Seg-Net) for infection classification. In this study, various DL models, including ResNet, SegNet, and UNet, were evaluated for their effectiveness in diagnosing COVID-19 infection using a real-time dataset of lung CT images. The proposed Inf-Seg-Net model demonstrated promising results, providing high-quality masking on the lung segmentation images. It achieved remarkable performance metrics, including 98.06% accuracy, 96.15% Jaccard index, 100% sensitivity, 98.1% precision, and 98.73% F1 score, indicating its potential for detecting infections from CT scans and outperforming existing models. These findings highlight the potential of AI and DL techniques in enhancing COVID-19 diagnosis and pave the way for more efficient and accurate screening methods.

Keywords
COVID-19, CT images, Deep learning, Infection segmentation.

1.Introduction
A significant number of lives and resources have been lost worldwide as a result of the novel coronavirus SARS-CoV-2, which causes COVID-19. Humans are at considerable risk for lung inflammation [1]. With symptoms ranging from minor respiratory distress to severe pneumonia and organ failure in people, the clinical presentation of COVID-19 is quite variable. Early-stage diagnosis techniques must be both extremely effective and reasonably priced given the rate at which illnesses are spreading among people.

For patients to get appropriate care and for the disease to be controlled, early and accurate diagnosis of afflicted areas is essential [2, 3].

Finding people who may be COVID-19 infected depends heavily on the screening method. Diagnostic tests, epidemiology histories, and symptom-based assessments are frequently used in COVID-19 screening. People are questioned about their symptoms and any recent contact with known or suspected COVID-19 cases during the screening process. The main goal of screening is to spot possible patients early, isolate them, and start the necessary transmission-prevention procedures.

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The screening process is not complete without diagnostic tests. Reverse transcription polymerase chain reaction (RT-PCR) testing is the most typical diagnostic procedure for COVID-19. This test can identify the SARS-CoV-2 virus' genetic material ribonucleic acid (RNA) in respiratory specimens. While negative screening findings may not completely rule out the possibility of infection, positive results suggest a higher likelihood of COVID-19 infection.

The RT-PCR test is frequently utilised as a COVID-19 diagnostic tool. This testing approach does have some drawbacks, though, including the potential for false negative results, difficulty with sample collection, and sensitivity and specificity issues. Results from RT-PCR testing take longer to receive since laboratory processing is necessary for precise results. This procedure uses a lot of resources because it needs specialised lab tools, knowledgeable workers, and certain reagents. Various factors, including sample transportation, laboratory workload, and the availability of resources, might affect how long it takes to get test results. These restrictions run the risk of spreading the infection farther and creating a false sense of security.

Hospitals frequently use computed tomography (CT) scans because they can perform early screening, identify sick tissues, and demonstrate sensitivity for the COVID-19 diagnosis [4, 5]. These CT pictures are used by radiologists to determine whether COVID-19 is present and how severe it is. In order to isolate COVID-19 patients as quickly as feasible, patients must be distinguished from normal participants. Prioritising individuals who require immediate medical attention can be made easier for medical providers by quantifying the severity of COVID-19 among subjects. As a result, the radiologists need a lot of evaluation time to locate and measure the infection. The main objective is to assess the challenges and prospective research directions associated with the use of chest CT slices for COVID-19 infection detection in the lungs. When it comes to the diagnosis and treatment of COVID-19, CT scans have a number of advantages over RT-PCR assays. Visual evidence of COVID-19-related lung abnormalities, such as ground-glass opacities, consolidations, and recognisable patterns, can be seen on CT scans. Even in asymptomatic or early-stage infections, this visual examination helps to identify COVID-19-related lung damage that may not be seen with RT-PCR assays alone. In order to track changes in lung involvement over time, CT scans are used to give a longitudinal assessment of disease development. When making clinical decisions and monitoring patients, it is helpful to know how they are responding to treatment. CT scans can aid in differential diagnosis, help distinguish COVID-19 from other respiratory disorders, and provide data for research and epidemiological studies.

Accurate identification and localizing the infected regions remain a challenge due to the similarities in intensity between normal and affected tissues, even for experienced radiologists and doctors [6]. Numerous studies concentrate on the COVID-19's clinical diagnostic features, particularly in the context of segmentation methods. This study aims to investigate and assess the efficiency of segmentation techniques in detecting and quantifying COVID-19 infections in medical imaging, such as chest CT scans. It takes a lot of time and effort to manually observe lung texture details for feature extraction. Artificial intelligence (AI) and machine learning (ML) approaches are used in computer-aided diagnostic (CAD) systems to detect minute variations between the two entities in order to speed up this task [7]. By combining different categorization approaches, the CAD approach considerably increases diagnostic accuracy and helps specialists and medical professionals finish complex jobs faster [8]. For testing and analysis, slices of chest CT from healthy and COVID-19-infected patients are gathered. Lung segmentation is required to separate lung areas from CT slices. To perform segmentation for identification and severity quantification of COVID-19, which can be an addition to traditional medical diagnostic methods, an automatic COVID-19 segmentation model based on AI must be trained. There is still need for improvement in terms of quick, accurate, and reliable infection identification and severity classification, despite the fact that numerous studies have found promising solutions for autonomous AI-based diagnosis. Therefore, the goal of this research is to investigate deep learning (DL) models and develop a new framework that performs better at infection detection.

In this research, a new infection segmentation network (Inf-Seg-Net) is proposed for segmenting the COVID-19-affected portions of the lungs using CT image slices, based on DenseUNet with residual blocks. A UNet [9], Dense Net [10], and ResNet [11] are all combined in this model. The usage of skip connections in residual blocks combined with dense layers will make it easier to train the dense network with fewer parameters. In the fight against COVID-

19, the suggested strategy has the power to transform the healthcare sector and enhance patient outcomes. A promising method for the early and precise detection of COVID-19 infections is thus provided by the suggested Inf-Seg-Net, which exhibits increased empirical performance of infection segmentation with faster computations.

The organizational structure of this research paper comprises several sections. Section 2 provides a summary of previous investigations. Section 3 outlines the research methods employed in this study. Section 4 presents the experimental assessment results. Section 5 contains a detailed discussion of the findings. Finally, Section 6 concludes the paper by summarizing the study and outlining potential future work.

2.Literature review

Infection segmentation using CT scan images is gaining popularity in recent times due to need for automatic segmentation of infections in the COVID-19 patients. Several models based on AI have been put forth in the last few years. In this section, a few works on segmentation are reviewed.

Earlier papers focused on segmenting the lungs precisely, since lung segmentation stands as the preceding step of infection segmentation. Shen et al. [12] proposed an automated system of lung segmentation on the basis of bidirectional chain code to enhance the effectiveness of the lung segmentation model. Nevertheless, the similar visual appearance of the background and nodules makes it tedious to extract the areas of the nodule. Jin et al. [13] employed data synthesized using generative adversarial networks (GAN) to enhance the training of a discriminative system for pathological localization of the lung. In order to embed the nodules within the background, the GAN was conditioned based on the region of interest (ROI), whose central portion comprising the nodule has been deleted.

A modified inception neural network (MINN) was presented by Wang et al. [14] to distinguish COVID-19 cases from healthy individuals. Instead of using the complete database of CT slices for training. Using ROIs that radiologists discovered using pneumonia features, a model was developed. Accordingly, the literature contends that applying AI to the lesion locations in chest CT scan pictures produces quantitative characteristics that can be used for COVID-19 large-scale screening [15], severity

evaluation, and lung infection quantification [16]. In order to create training pairs for a normalcy-recognizing network (NormNet), Yao et al. [17] synthesised 'lesions' using a handful of straightforward operations and inserted the resulting 'lesions' into typical CT lung scans. This allowed NormNet to distinguish between normal tissues and potential COVID-19 lesions.

Gao et al. [18] this paper investigates an approach to enhance the accuracy of COVID-19 diagnosis and lesion segmentation using CT images. The Dual-branch Combination Network (DCN) framework is used to leverages the strengths of DL algorithms for both diagnostic classification and lesion segmentation. By combining the two branches, the DCN aims to provide more reliable and precise results for COVID-19 detection and localization in CT scans. For the accurate detection and localisation of COVID-19 infections in chest CT images, Jeevitha and Valarmathi [19] offer a system that combines both segmentation and classification tasks. The approach seeks to overcome the difficulties in diagnosing COVID-19, including the requirement for accurate lung infection segmentation and accurate classification of infected regions. This project intends to improve the overall performance and effectiveness of COVID-19 detection systems by integrating these two functions into a single framework. The suggested method uses convolutional neural networks (CNNs), a DL technology, for both segmentation and classification tasks, allowing for the simultaneous identification of contaminated areas and the precise detection of COVID-19 cases.

Lung segmentation, a vital stage in the automated processing of lung scan pictures, is the subject of Kordnoori et al. [20]. The suggested method makes use of a DL framework that combines numerous related tasks, allowing for collaborative learning and information exchange between various parts of lung study. The model intends to increase the accuracy and robustness of lung segmentation, hence permitting more efficient analysis and diagnosis of Covid-19 disease based on lung scan imaging data. This is done by utilising the interdependencies between jobs. A DL model named DeepCoV is proposed by Roy and Das [21] for the detection of COVID-19 utilising both chest X-ray (CXR) and CT images. Lung segmentation, which tries to precisely identify and isolate the lung region in the input pictures, is a vital part of the Deep-CoV model. In order to pinpoint probable COVID-19-related problems and for more accurate analysis, lung

segmentation is crucial. To achieve precise lung segmentation, it combines DL algorithms with cutting-edge image processing techniques.

An automated diagnosis system for COVID stages is presented by Patel and Kashyap [22] using texture-based Gabor features in variational mode decomposition from CT scans. The authors use Gabor filters to extract discriminative texture features from the CT images after breaking them down into texture and structure components. These characteristics provide the data for a classification model that classifies the various COVID stages automatically. For precise detection, Kannan et al. [23] suggest combining an attention segmental recurrent neural network (ASRNN) with the Archimedes optimisation algorithm. The Archimedes optimisation approach improves the ASRNN's performance and convergence while capturing pertinent contextual data from the CT images. This method combines DL and optimisation techniques for efficient identification, making a contribution to the field of Covid-19 diagnostics. Abualigah et al. [24] segmentation of CT images is a critical task in medical image analysis as it helps in identifying and isolating regions of interest, such as lung abnormalities. A new evolutionary arithmetic optimization algorithm for the multilevel thresholding is used for segmentation of COVID-19 CT images.

In COVID-19 CT scans, Ilhan et al. [25] suggested a method for lung segmentation. To provide precise and dependable segmentation results, they integrate a U-Net model with localization and augmentation techniques. The lung ROI is located using the localization method, which enables the segmentation process to concentrate particularly on the lung region. In order to aid in the accurate identification of lung structures, enhancing techniques are also used to increase the visibility and clarity of lung boundaries. A method for lung segmentation is suggested by Suvathi et al. [26] in order to increase the precision of COVID-19 categorization. The need of precise lung segmentation is emphasised by the authors as an essential preprocessing step for accurate COVID-19 diagnosis and classification. They create a lung segmentation programme using DL methods that successfully distinguishes between different lung areas in chest radiography. The suggested method exhibits strong performance in accurately segmenting lung areas, even in the presence of COVID-19-related anomalies, by using a CNN architecture.

Jyoti et al. [27] preprocessing, feature extraction, and classification are its three basic phases. Improve the contrast and sharpness of the input X-ray pictures during preprocessing. To extract distinguishing features from the preprocessed images, they next use the time-variant quaternion wavelet transform (TQWT) algorithm. The multiple component analysis (MCA) algorithm reduces the dimensionality of the feature space. TQWT and MCA to determine if CXR pictures are positive or negative for COVID-19. Jia et al. [28] the technique entails teaching a CNN to segment COVID-19 lesions in CT images using pixel-by-pixel sparse graph reasoning. The CNN model incorporates pixel-wise sparse graphs to collect both local and global contextual information. By taking use of the correlations between nearby pixels in the image, the model learns to categorise and segment COVID-19 lesions. A collection of labelled CT scans is used to train the model, and rigorous training and validation procedures are used to optimise performance. Gupta and Bajaj [29] for the automated screening of COVID-19, they use three separate DL models: MobileNetV2, DarkNet19, and a newly created lightweight DL Model. A repeated ten-fold holdout validation procedure is used, which entails training, validating, and testing the DL Models, to assess how well these models function.

Constantinou et al. [30] using transfer learning techniques, COVID-19 classification of CXR images is performed. InceptionV3, ResNet50, ResNet101, DenseNet121, and DenseNet169. This work uses lung segmentation and localization techniques on CXR images to improve the classification accuracy of the system. They will test an ensemble model and increase the robustness and generalizability of the system to new CXR images. The Choudhary et al. [31] method uses the transfer learning-based DL VGG16 and ResNet34 Models to overcome the difficulties of COVID-19 CT scan categorization. Their method of concentrating on crucial weights throughout the fine-tuning phase, which reduces computational complexity while retaining classification accuracy, is their significant contribution. Albataineh et al. [32] study, CT scans are used to train ML algorithms for COVID-19 diagnosis and severity assessment. Support vector machines (SVM), random forests, and DL models are some of the algorithms that are used to extract features and classify the CT images into several groups. Annotated CT image datasets are used to train the models, and rigorous training and validation procedures are used to optimise performance. Ren et al. [33] uses medical pictures, a Transformer model is

trained for the classification of COVID-19 patients. The Transformer architecture, which was created initially for challenges involving natural language processing, has been modified for use with medical pictures. In order to categorise the photos into COVID-19 positive or negative categories, the model learns to extract spatial and contextual information from the photographs. A dataset of medical picture labels is used to train the model, and it is then tweaked to function as well as possible. Mukhi et al.

[34] Information from many imaging modalities, such as CT scans, X-rays, and molecular imaging, is included in the multimodal data. CNN models such the VGG-19, ResNet-50, Inception v3 and Xception models are utilised to extract pertinent features from the multimodal data and classify COVID-19 instances using optimised DL approaches. The *Table 1* encompasses important aspects such as the models used, as well as the advantages and limitations associated with each study.

Table 1 Presents a comprehensive overview of various studies conducted on COVID-19 lung segmentation

References	Model	Description	Advantages	Limitation
Fan et al. [35]	Inf-Net, Semi-Inf-Net	The Inf-Net, a deep network for segmenting COVID-19 lung infections in CT slices, utilizes a parallel partial decoder to aggregate features and generate a global map for initial guidance. To enhance boundary cues, the model incorporates implicitly recurrent reverse attention modules and explicit edge-attention guidance to establish area-to-boundary relationships. To address the limited availability of labeled data, a semi-supervised segmentation system for COVID-19 infection segmentation.	The proposed Inf-Net and Semi-Inf-Net networks offer advantages in COVID-19 infection segmentation. They utilize reverse attention and edge-attention to enhance infected region identification. The semi-supervised solution helps overcome the shortage of labeled data.	The multi-class infection labelling strategy may lead to sub-optimal learning. Additionally, accuracy may drop for non-infected slices.
Bougourzi et al. [36]	PDAtt-Unet	PDAtt-Unet is a technique for precise segmentation of COVID-19 infections from CT scans that combines the Unet architecture with pyramid dual-decoder attention techniques. While the decoder creates segmentation masks, the encoder gathers high-level information from the CT scan pictures. Attention mechanisms are employed to highlight relevant features and suppress irrelevant information, further enhancing the segmentation.	It reduces the time and effort required for manual analysis, enabling faster diagnosis and decision-making.	The approach has potential challenges and lack in decoder-encoder architecture
Chen et al. [37]	Teacher-student framework with Fourier Transform augmentation	To accurately segment COVID-19 infections in CT scans, the method integrates a teacher-student architecture with Fourier Transform augmentation. Pre-trained segmentation model called the teacher network creates fictitious labels for unlabelled data. Labelled data and	The transfer of knowledge enhances the student model's segmentation accuracy for COVID-19 infections. The use of Fourier Transform-based data augmentation techniques provides additional variations in the training data. This augmentation can enhance the model's robustness to different	The infection segmentation relies on the availability of annotations for lung CT with pulmonary nodules but lacks pixel-wise annotations specifically for COVID-19 CT images. Although a Fourier Transform-based augmentation method is introduced to alleviate intensity differences, it lacks that the approach may not fully capture the

References	Model	Description	Advantages	Limitation
		pseudo-labelled data produced by the teacher network are used to train the student network. The training data is also enhanced using the Fourier Transform, which increases the model's robustness.	CT image characteristics	unique characteristics of COVID-19 infections
Chen et al. [38]	DNN – 3D U-Net	An efficient deep neural network (DNN) using a 3D U-Net architecture. An encoder and a decoder that are connected by skip links make up the DNN. Convolutional layers are used by the encoder to extract high-level features from the input images, while deconvolutional layers are used by the decoder to reconstruct the segmentation masks. The precision of segmentation is increased by the skip connections, which allow the decoder to include low-level characteristics from the encoder.	The combination of ROI extraction, 3-D network with attention model, combination loss function, and data augmentation results in the highest performance make it a promising tool for accurate and reliable lung lesion segmentation.	The application of conditional random field (CRF) in postprocessing improves the accuracy of voxel point classification near the boundary, there might be limitations in cases where the correlation between voxels is complex or the boundary is highly ambiguous.
Selvaraj et al. [39]	Covid-screen-Net	A DNN model trained on a limited dataset. The model utilizes region-specific approaches like Zernike moment and gray level co-occurrence matrix to extract shape and texture features for segmentation	The DNN model has its ability to achieve improved performance with a smaller number of training points compared to other popular deep networks. This advantage allows for more efficient training, reducing the requirement for a large training dataset while still providing effective detection of COVID-19 infections in the lungs.	DNN model for COVID-19 detection from lung CT axial view images is the difficulty in detecting ground-glass opacities (GGO) from poor contrast CT images. This limitation hinders the model's ability to provide detailed information and accurate detection in cases with low contrast.
Ter-Sarkisov [40]	Region-based convolutional neural networks (R-CNN)	The approach analyze chest CT scans, enabling the identification and segmentation of lesion areas associated with COVID-19 infections merging lesion masks for Ground Glass Opacity and Consolidation into a single mask improves the predictive power and precision of the instance segmentation model	The finding provides valuable insights for accurately identifying and segmenting different types of lesions, enhancing the performance and effectiveness of the segmentation model.	Factors such as potential difficulties in accurately delineating lesion boundaries, handling variations in lesion size, shape, and appearance, or potential limitations in handling complex cases with overlapping or ambiguous lesions are not explicitly mentioned. Understanding these limitations is crucial for assessing the reliability and generalizability of the segmentation.

A summary of several methods and procedures for COVID-19 detection and infection segmentation using CT scan images is given in the literature review. Lung segmentation has received a lot of attention as a foundational stage in infection segmentation. The focus of other studies has been on locating anomalies and lesions in the lungs. For lung segmentation, a number of deep-learning models and architectures have been suggested. For COVID-19 detection, some studies have also included segmentation and classification tasks. For better segmentation and detection of COVID-19 infections, methods like texture-based feature extraction, attention processes, and teacher-student frameworks

have also been investigated. Overall, these findings show the increased demand for using DL methods and cutting-edge algorithms for COVID-19 identification and infection segmentation in CT scan images.

3. Materials and methods

Figure 1 shows the segmentation of the COVID-19 infection suggested framework. The framework's subsequent phases are designed to offer a methodical methodology for precisely identifying and analyzing infections in lung CT images. First, using the contrast limited adaptive histogram equalization based on non-local mean filter (CLAHEN) filter the input lung

CT image is preprocessed to reduce noise. By improving the image's quality, this phase ensures superior segmentation outcomes. The preprocessed image is then subjected to the logarithmic non-maxima suppression (LNMS) method of lung segmentation. This method successfully spots and isolates the lungs within an image, which is a crucial step for later infection segmentation. The trained Inf-Seg-Net model receives information from the model on the presence of infection in the lung regions. The final infection segmented resulting image is created by superimposing the segmented infections over the original image.
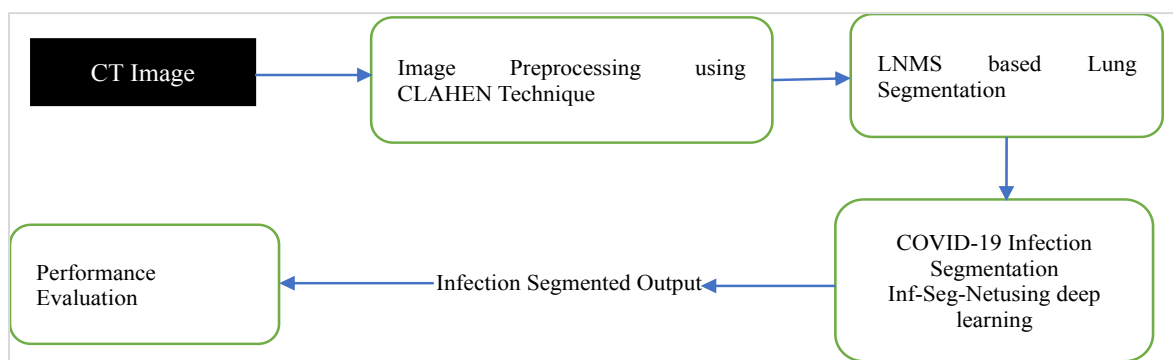
Figure 1 Proposed framework of COVID-19 infection segmentation

3.1 Dataset description

The axial view chest CT scans was chosen due to its widespread usage by radiologists for clinical diagnosis. The dataset utilized for training and evaluating the proposed model was provided by Medi Lab, offering real-time data. Initially, a collection of 300 photos was acquired for utilization in this study. The dataset encompasses four distinct classes, representing normal, mild, moderate, and severe cases, in order to accurately reflect the range of conditions encountered. By incorporating these distinct categories into the dataset, the researchers aimed to capture the full spectrum of chest pathologies encountered in clinical practice. To ensure the effectiveness and generalizability of the proposed model, the gathered dataset was divided into two main subsets: a training set and a testing set. The segmentation network employed for this research allocated 80% of the dataset for training purposes, while the remaining 20% was reserved for testing and evaluating the model's performance.

3.2 Pre-processing using CLAHEN technique

This stage involves applying the CLAHEN approach to remove noise from the input lung CT images. This

CLAHEN algorithm combines CLAHE with a non-local means (NLM) filter. Using CLAHE to boost contrast, this technique then uses a NLM filter to cut down on noise and maintain image features. This works on tiny chunks of the image called tiles rather than the complete image. Then, to remove false borders, the nearby tiles are added using the bilinear interpolation technique. The histogram equalisation method and NLM filtration method are both used to process each individual pixel of the image in order to reduce noise and enhance contrast. Equation 1 can be used to express the contextual region of the image tile's contrast-limited histogram as follows:

$$N_{avg,i} = \frac{N_x \times N_y}{N_{gray}} \qquad (1)$$

Where, N_avg represents the average count of pixels in the image tile i, N_gray represents the count of gray pixels in the contextual area, N_x and N_y are the count of pixels in X and Y dimensions, respectively.
The NLM filtered image tile can be expressed in Equation 2,

$$nlmfTile_i(p) = \frac{1}{C(p)} \int_{q=1}^{\Omega} u(q)w(p,q)\,d \qquad (2)$$

Where, nlmfTile$_i$ (p) is the filtered image tile i at pixel p, u(q) denotes the unfiltered image tile at pixel q, w(p,q) denotes the weighting function, and C(p) represents the normalization factor expressed in Equation 3,

$$C(p) = \int_{q=1}^{\Omega} w(p,q) \ dq \qquad (3)$$

The procedure of preprocessing through CLAHEN technique is given in algorithm 1 as follows.

Algorithm 1: Preprocessing CT Slices using CLAHEN	
Input:	Input Chest CT Slice
Output:	CLAHEN Preprocessed Image
1:	Load Input Image $Image$
2:	$Tile = generateTiles(Image, n)$
3:	**for** $i = 1\ to\ n$
4:	$histTile_i = histogram(Tile_i)$
5:	$evTile_i = excessiveEvaluation(histTile_i)$
6:	$edTile_i = excessiveDistribution(evTile_i)$
7:	$erTile_i = excessiveRedistribution(edTile_i)$
8:	$cdfTile_i = CDF(erTile_i)$
9:	$nlmfTile_i = NLMF(cdfTile_i)$
10:	**end**
11:	$pImage = bilinearInterpolation(Tile)$
12:	Return $pImage$

The process begins by loading a chest CT slice image and utilising the "Generate Tiles" tool to divide it into smaller tiles. The "histogram" function, together with the "excessive Evaluation" and "excessive Distribution" functions, are used to construct the histogram for each tile. The distribution of pixel intensities inside a tile is represented by the histogram function. Each tile's histogram is subjected to excessive evaluation in order to examine its features and shape. The histogram is further redistributed by the excessive distribution function, highlighting the distinction between pixel intensities and boosting contrast. The cumulative distribution function (CDF) created from the redistributed histogram is next passed to the "NLMF" function. Bilinear interpolation is then used to recreate the preprocessed image. The proposed CLAHEN approach prevents edge blurring by sharpening the edges and boosting the image's contrast. Additionally, the NLM filter gives the final image added clarity through filtering. This suggested CLAHEN approach not only produces contrast-enhanced images but also blurs noisy pixels and sharpens edges.

3.3 LNMS based lung segmentation
The proposed technique for lung segmentation includes the subsequent steps: Thresholding, gradient calculation to obtain the magnitude and orientation of the gradients in the image, LNMS approach to obtain the position and unilateral edges from the image, double threshold approach for precisely detecting and connecting the edges of the lungs, and the final lung mask extraction procedure. LNMS is an algorithm used to detect object tasks to improve the accuracy and efficiency of bounding box detection. The procedure for LNMS based lung segmentation is illustrated in the following algorithm 2.

Algorithm 2: Lung Segmentation using LNMS	
Input:	CLAHEN Preprocessed Image
Output:	Lung Segmented Image
1:	Load Preprocessed Image $pImage$
2:	Initialize $Thres$
3:	$binImage = pImage < Thres$
4:	$gaussImage = gaussian(binImage)$
5:	$magG = magnitude(gaussImage)$
6:	$oriG = log(location(magG))$
7:	$eImg = connectedges(magG, oriG)$
8:	$cImg = imclearborder(eImg)$
9:	$lImg = extractblobs(cImg)$
10:	$lungs = imfill(lImg)$
11:	$elungs = imerode(lungs)$
12:	$segLungs = mask(elungs)$
13:	$supLungs = superimposition(segLungs)$
14:	Return $supLungs$

There are various steps in the segmentation of the lungs. First, loading the preprocessed picture and initialising the threshold value are necessary for lung segmentation using LNMS. To create a binary image, the preprocessed image is then thresholded using the threshold value. The binary image is then given a Gaussian filter to eliminate noise and soften the edges. The filtered image's magnitude and orientation are then computed. These numbers are utilised to identify the image's edges, and the border regions are cleaned to get rid of any noise or artefacts there may be.

The lung portions are subsequently identified by filling in the confined parts around the removed margins, which are now blobs. To further process the detected lung regions, they are eroded to isolate the lungs from any surrounding regions. The segmented lungs are then overlaid on the original image after being masked to remove any undesirable areas. The lung segmentation process is completed by returning the overlay image.

The detection and segmentation of lungs in medical CT scans, an essential step in many diagnostic and therapeutic procedures, has demonstrated excellent results for this approach.

3.4 Inf-Seg-Net based lung infection segmentation

A suggested DL model called Inf-Seg-Net for segmenting COVID-19 infections is based on the combination of UNet, DenseNet, and ResNet. UNet is a multi-scale CNN architecture with channel-wise concatenation capabilities. The element-wise summation practised in fully connected networks (FCNs) is replaced by channel-wise concatenation, which appends the feature maps of the expanding and contracting paths. Due to the UNet model's exceptional success in expanding the field of receptivity by minimising feature mappings, it has a low computational cost and memory requirement. On the other hand, the UNet frequently has a lot of parameters. As a result of the vanishing gradient problem, this makes UNet more challenging to train and restricts its functionality. To overcome these difficulties, DenseUNet [21] was developed. The DenseUNet method effectively utilises the benefits of both DenseNet and UNet. Utilising weighted loss, the DenseUNet improves segmentation effectiveness. On the other hand, DenseUNet has dense layers, which can increase the computing complexity of the network. In order to train the dense network with fewer parameters, this study advises modifying the DenseUNet by adding residual blocks with skip connections. The recommended Inf-Seg-Net model makes use of denser layers, weighted loss to enhance the segmentation function, and residual skip connections to reduce computing complexity to increase performance. Equation 4 allows for the expression of the suggested Inf-Seg-Net model's loss function.

$$L(i,j) = \frac{\Sigma_{i,j}(m_{i,j}p_{i,j})}{\Sigma_{i,j}(m_{i,j})^2 + \Sigma_{i,j}(p_{i,j})^2 - \Sigma_{i,j}(m_{i,j}p_{i,j})} \qquad (4)$$

Where, $m_{i,j}$ is the ground truth mask value (1 for infection and 0 for background) of pixel location (i,j), and $p_{i,j}$ is the confidence measure of the network that the pixel at the location (i,j) is infection. *Figure 2* depicts the suggested Inf-Seg-Net model architecture.
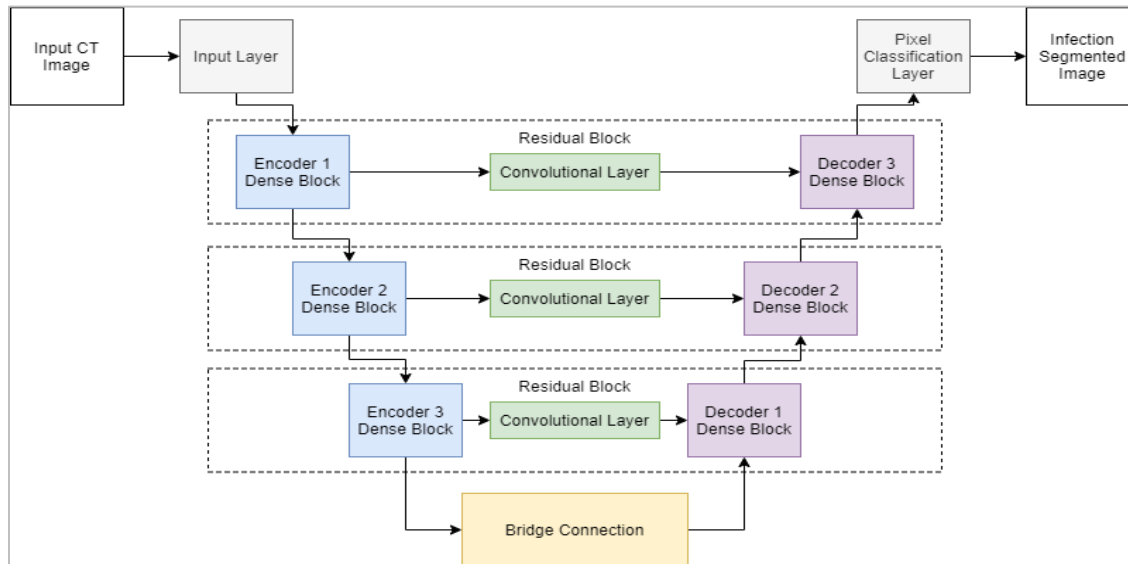

Figure 2 The proposed Inf-Seg-Net model architecture

The procedure of infection segmentation using Inf-Seg-Net is presented in algorithm 3 as follows.
The Inf-Seg-Net algorithm for infection segmentation involves several steps: preparing the data, labelling the images, training and evaluating the network, and returning the predicted segmentation. The procedure for infection segmentation using Inf-Seg-Net is explained below.

Step 1: Manual Pixel Labelling for the Dataset
First, a lung segmented image is prepared. The supLungs dataset is loaded in the ImageLabeler application of MATLAB and an image labelling session is started. With the help of a radiologist, for each image, infection pixels and background are labelled using assisted freehand tool. These pixel-labelled output images are the ground truth images for the dataset. The labelled images are then saved in

a separate folder, and the dataset is split into training and test sets.

Step 2: Loading Segmentation Network
The proposed Inf-Seg-Net is used for segmenting infections present in the lungs. The developed model contain layers such as image input layer, Convolutional layer, relu activation layer, max pooling layer, followed by the convolutional layer, relu activation layer, transposed convolutional layer, convolutional layer, softmax layer, and pixel classification layer.

Step 3: Training
The layers and training options for Inf-Seg-Net are initialized, and the network is trained using the training dataset along with the corresponding prepared ground truth images. The network is trained after initializing hyper parameters such as learning rate, maximum epochs, verbose frequency, etc., which are shown in the below *Table 2*.

Algorithm 3: Infection Segmentation using Inf-Seg-Net	
Input:	Lung Segmented Image
Output:	Infection Segmented Image
1:	Open *ImageLabeler* application
2:	Start an *imagelabelling* session
3:	Load the folder of $supLungs$ of whole dataset
4:	**for** $i = 1\ to\ n$
5:	Label Infections in $supLungs_i$
6:	Label Background in $supLungs_i$
7:	**end**
8:	Save labelled images $labelImages$ in a separate folder
9:	$[trainset, testset] = split(labelImages)$
10:	Initialize the $layers$ of Inf-Seg-Net
11:	Initialize the $trainingOptions$ of Inf-Seg-Net
12:	$net = train(trainset, layers, trainingOptions)$
13:	$Ypred = classify(net, Xtestset)$
14:	$performance = evaluate(Ypred, Ytestset)$
15:	Return $Ypred$

Table 2 Training parameter and its value

Hyperparameter	Value
Learning rate	0.001
Max epochs	25
Verbose frequency	2
Mini batch size	4
Optimizer	Adam

Step 4: Testing
Once the network is trained, it is tested using the testing dataset which does not contain the ground truth images. The performance of the Inf-Seg-Net on the testing dataset is evaluated in terms of accuracy, intersection over union (IoU) (otherwise known as Jaccard Index), sensitivity, precision, and dice coefficient (otherwise known as F1 Score).

4.Results
The proposed COVID-19 infection segmentation is carried out using the DL and image processing toolboxes implemented in MATLAB R2020a. The proposed DL framework includes noise removal based on CLAHEN, lung segmentation based on LNMS, and infection segmentation based on Inf-Seg-Net.

Table 3 shows a comparison between the number of images before and after preprocessing using the CLAHEN algorithm. The "Existing" column indicates the number of images in the dataset before preprocessing, while the "After" column shows the number of images remaining after preprocessing.

Table 3 Comparison between existing and proposed CLAHEN preprocessing method

	Before Preprocessing (images)	After Preprocessing (images)
Existing Method	300	150
Proposed CLAHEN Method	300	198
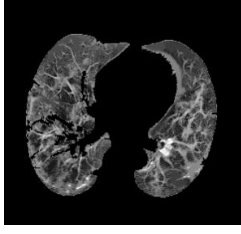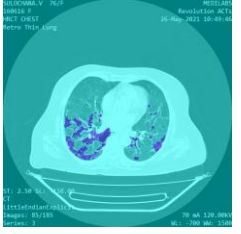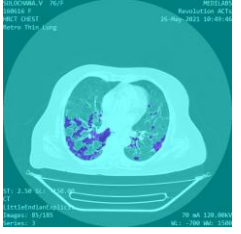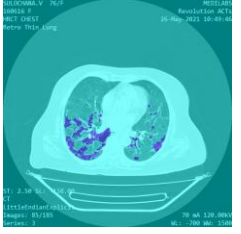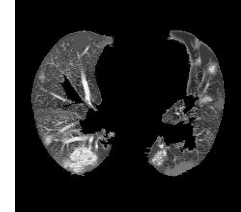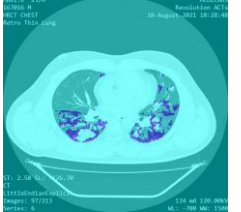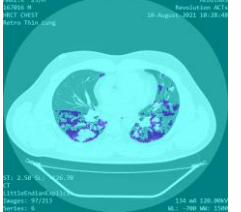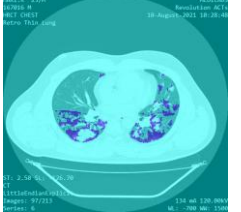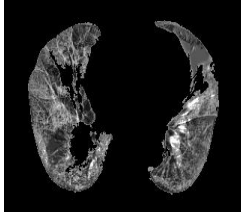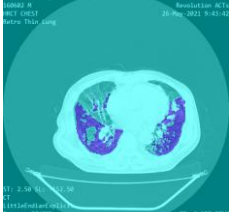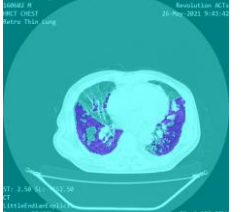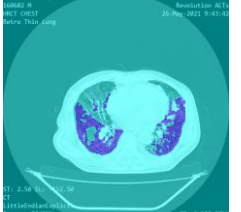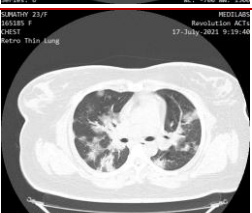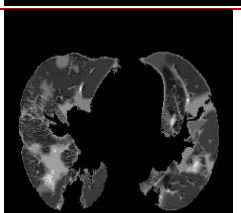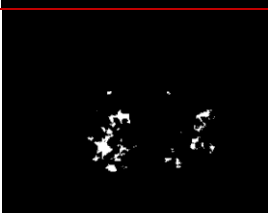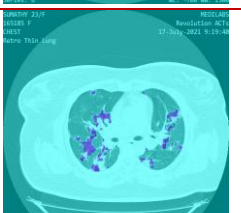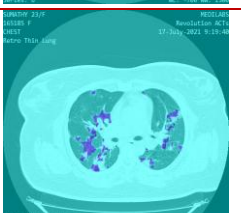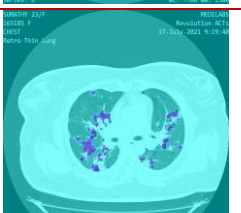
Table 4 shows the comparison of the results of existing models and a proposed Inf-Seg-Net model in terms of segmented images.

Table 4 Comparison between Existing and Proposed Inf-Seg-Net Segmentation Methods

	SegNet	ResNet	UNet	Proposed Inf-Seg-Net
Input Images	150	150	150	150
Segmented Images	120	135	144	147

For a sample of 4 input CT slices, *Table 5* shows the results for each stage, including pre-processing, lung segmentation, infection segmentation, and infection superimposition.

Table 5 Results of the proposed DL framework

Input CT slice	Lung segmented image	Infection Segmented image	Infection image	Superimposed

Inf-Seg-Net's performance was compared to that of existing CNN architectures such as UNet [9], SegNet [41], and ResNet [42]. Following is a tabulation of the comparative analysis outcomes in *Table 6.*

The segmentation accuracy of an infection is determined by comparing each pixel of the segmented image to its corresponding pixel in the ground truth image. The proportion of correctly classified pixels to the total number of pixels is the accuracy score. This is represented in Equation 5.

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \qquad (5)$$

Where, T_P is True Positives, T_N is True Negatives, F_P is False Positives, and F_N is False Negatives.

Another accuracy metric is the IoU (also known as Jaccard Index), which is determined using Equation 6 and the ratio of T_P to the total of T_P, F_P, and F_N.

$$IoU = \frac{T_P}{T_P + F_P + F_N} \qquad (6)$$

Sensitivity is defined as the probability of the positive test, that is conditioned on being T_P. This can be evaluated by the Equation 7 as,

$$Sensitivity = \frac{T_P}{T_P + F_N} \qquad (7)$$

Precision shows the measure of how of positively classified observations are relevant. This can be expressed as given in Equation 8 as follows,

$$Precision = \frac{T_P}{T_P + F_P} \qquad (8)$$

F1-score is the measure of test accuracy calculated using precision and sensitivity. The formula for F1-score is given in Equation 9.

$$F1 - score = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity} \quad (9)$$

Error rate is a measure of the model's incorrect predictions. It is calculated by dividing the number of inaccurate predictions by the total number of predictions made by the classifier is given in Equation 10.

$$Error\ rate = \frac{F_P + F_N}{T_P + T_N + F_P + F_N} \quad (10)$$

G-mean: Calculate the geometric mean, which is useful when dealing with imbalanced datasets. It combines sensitivity (true positive rate) and specificity (true negative rate) is given in the Equation 11.

$$G\_mean = \sqrt{sensitivity \times specificity} \quad (11)$$

In *Table 7*, we have conducted a comparative analysis of our method with several existing approaches that utilize deep networks for segmenting the COVID-19 infected region from CT image datasets.

Figure 3 provides a comparative analysis of different segmentation models based on multiple evaluation metrics. *Figure 4* demonstrates the varying execution times of the different models. Thus, results prove the proposed Inf-Seg-Net model performs better than conventional UNet, SegNet, and ResNet.

Table 6 Performance comparison of infection segmentation

Parameter	UNet	SegNet	ResNet	Proposed Inf-Seg-Net
Accuracy	97.02	62.41	80.63	98.06
Error rate	0.0298	0.3759	0.1936	0.0150
Intersection over Union	95.21	60.84	79.06	96.15
Sensitivity	98.8	62.53	82.11	99.37
Precision	98.1	98.64	97.80	98.1
F1score	98.48	76.54	89.27	98.73
G-mean	0.259	0.593	0.233	0.177
Execution time (s)	60.57	90.12	79.02	58.65

Table 7 Comparative analysis of proposed model with existing approach

Reference	Model	Accuracy (%)	Sensitivity (%)	Precision (%)	F1 Score (%)
[43]	MobileNetV2 Tuned	96	-	96	96
[44]	U-NET	-	96	-	73
[44]	SegNet	-	95	-	74
[45]	Enhanced COVID-Rate	-	80	-	83
[46]	AAF-U-Net	96	95	98	96
[47]	SAUNet++	-	93.28	-	87.54
Proposed	Inf-Seg-Net	98.06	99.37	98.1	98.73

5.Discussion

The CT image reveals an early lung lesion that a radiologist can use to diagnose. The purpose of identifying COVID-19 lesions is to reduce the radiologist's evaluation time. A solution based on AI offers a rapid, efficient, and trustworthy alternative for medical diagnostic strategies. The CLAHEN preprocessing result from *Table 2* shows that the "Existing" column indicates the number of images in the dataset before preprocessing, while the "After" column shows the number of images remaining after preprocessing. There were 200 images in the dataset; after preprocessing with existing methods, only 150 images remained. After applying CLAHEN, only 198 images remained. This suggests that CLAHEN preprocessing significantly reduces invalid images in the dataset and provides enhanced images.

The proposed Inf-Seg-Net Model is used to segment lung lesions with improved results. The proposed image separates the lung in addition to other segmented regions. The erode mask procedure is used to flatten the lung margins. The mask is applied to the input image in order to segment the lungs. The results from *Table 2* shows 150 images in the dataset, existing method ResNet shows only 135 images, UNet shows only 144 images, SegNet shows 120 images and proposed method shows 147 images. This suggests the proposed Inf-Seg-Net model efficiently segment the lung image.

The segmentation results demonstrate in *Figure 3* shows that the proposed Inf-Seg-Net model is superior to UNet in terms of accuracy, IoU, F1 score, and sensitivity by 0.2%, 0.17%, 0.1%, and 0.21%, respectively. ResNet and SegNet are performing less effectively than Inf-Seg-Net and UNet. The proposed Inf-Seg-Net model achieves 0.2%, 31.56%, and 24.5% greater infection segmentation accuracy than UNet, SegNet, and ResNet, respectively.

Figure 4 it shows that the geometric mean measures the central tendency of a set of values, providing insight into the overall performance of each model. In this context, the UNet model achieves a geometric mean of 0.259, indicating a moderate level of effectiveness in capturing the underlying patterns in the data. On the other hand, the SegNet model demonstrates a higher geometric mean of 0.593, suggesting better performance compared to UNet. However, the ResNet model exhibits a lower geometric mean of 0.233, indicating relatively

weaker predictive capability. Remarkably, the proposed Inf-Seg-Net model surpasses all other models, achieving a significantly improved geometric mean of 0.176. This implies that the proposed Inf-Seg-Net model excels in capturing important features and delivering more accurate predictions.

The error rate is a crucial parameter to evaluate the performance of different models. the UNet model demonstrates an error rate of 0.0298, indicating a relatively low level of errors in its predictions. The SegNet model, on the other hand, exhibits a higher error rate of 0.3759, suggesting a larger number of erroneous predictions. The ResNet model performs better than SegNet but falls short of UNet, with an error rate of 0.1936. However, the proposed Inf-Seg-Net model outperforms all the other models in terms of error rate, achieving an impressively low value of 0.0150. This suggests that the proposed Inf-Seg-Net model has the ability to make more accurate predictions and minimize errors effectively.
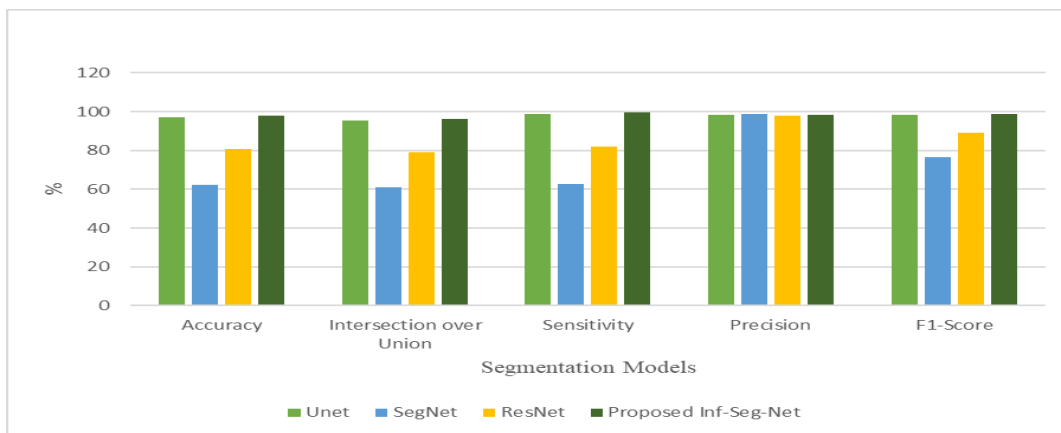

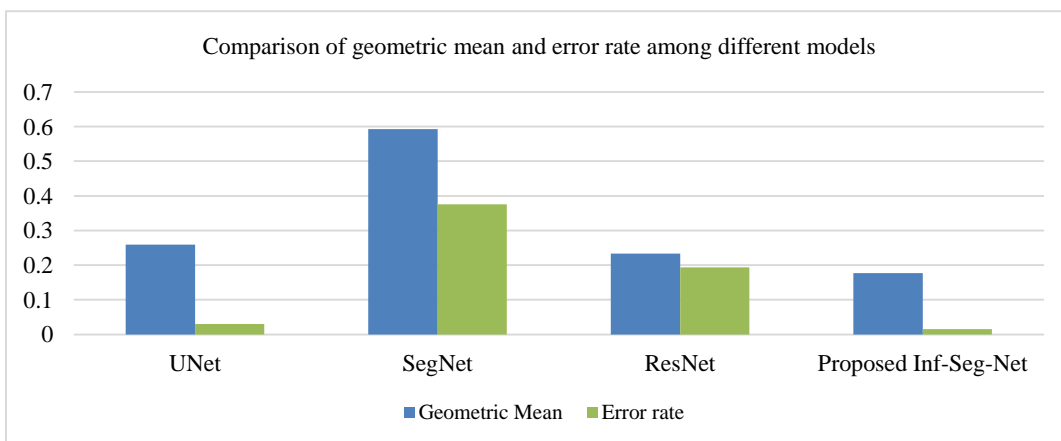**Figure 3** Performance comparison of infection segmentation models

Figure 4 Comparison of geometric mean and error rate

Figure 5 illustrates the comparison of execution time (in seconds) for four different models: UNet, SegNet, ResNet, and the proposed Inf-Seg-Net. UNet has the lowest execution time among the models, with a value of 60.57 seconds. The proposed Inf-Seg-Net follows closely behind with an execution time of 58.65 seconds. On the other hand, SegNet and ResNet exhibit higher execution times of 90.12 seconds and 79.02 seconds respectively. UNet and the proposed Inf-Seg-Net being the fastest, while SegNet and ResNet require more time to complete their execution.
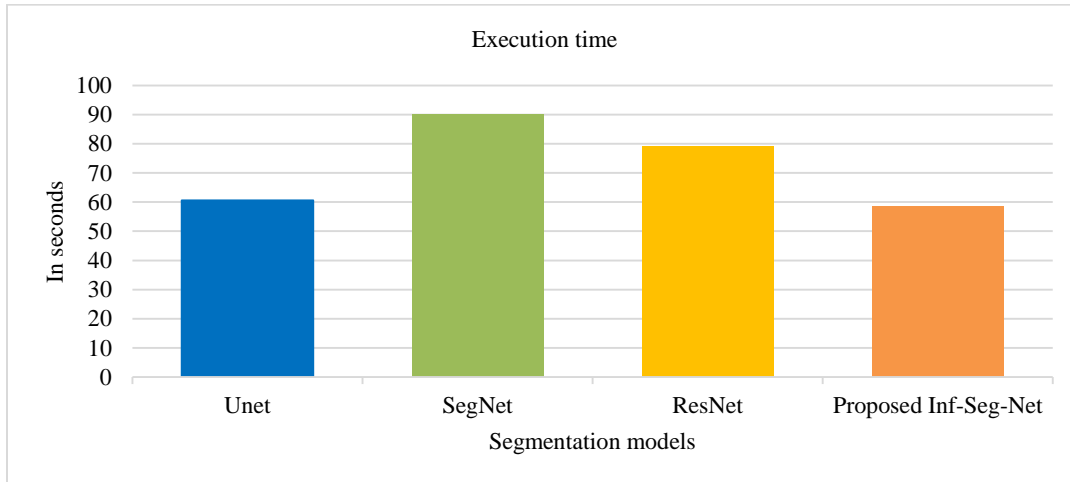

Figure 5 Comparison on total execution time

The proposed Inf-Seg-Net model for COVID-19 infection segmentation achieved high accuracy, sensitivity, precision, and F1 score. The model demonstrated an accuracy of 98.06%, a Jaccard index of 96.15%, 100% sensitivity, 98.1% precision, and a 99.02% F1 score. The dense with residual blocks architecture proved effective in segmenting infections in CT images. The results indicate that the proposed Inf-Seg-Net model can successfully detect and segment COVID-19 infections in lung CT scans. The high accuracy and performance metrics suggest that the model has the potential to aid in the early and accurate detection of COVID-19, which is crucial for effective treatment and control of the disease. The Dense UNet with Residual Blocks architecture, which combines the merits of UNet, Dense Net, and ResNet, proved to be a robust approach for infection segmentation. The proposed model has significant implications for the field of healthcare, particularly in the context of COVID-19 diagnosis. By automating the infection segmentation process, the model can assist radiologists and doctors in quickly and accurately identifying COVID-19 infections in CT scans. This can potentially improve the efficiency of diagnosis, reduce the burden on healthcare professionals, and enable timely isolation and treatment of infected individuals. The model can also contribute to research and epidemiological studies by providing a tool for quantifying the severity of COVID-19 infections.

There are several limitations of the proposed model was evaluated using a specific real-time dataset, and its generalizability to other datasets or populations needs to be further investigated. Further validation of diverse datasets is necessary to assess the model's robustness and reliability. To further enhance the proposed Inf-Seg-Net model it is recommended to conduct additional experiments on larger and more diverse datasets that can help assess the model's performance across different populations and imaging protocols. The segmentation of non-lung areas may still occur even though the erode mask process is used to flatten the lung boundaries due to the mask that was applied. In the future, we will focus on training the segmentation network with more sufficient COVID-19 data, including other modalities such as CXR and MRI to improve the segmentation performance further. Second, this work only involved the segmented COVID-19 infection in the lung. Theoretically, this method can be extended to other organs from CT images.

A complete list of abbreviations is shown in *Appendix I.*

6.Conclusion and future work

A CT scan can reveal early lung lesions and help radiologists make a diagnosis. To reduce radiologists' evaluation times, it is essential to detect COVID-19 lesions efficiently. AI-based technology offers a quick, effective, and reliable alternative to conventional medical diagnostic techniques. The proposed DL architecture suggests segmenting COVID-19-infected lung CT slices based on preprocessing, lungs, and lesions. The CLAHEN filter was successfully utilized in the preprocessing unit to reduce noise, enhance contrast, and preserve edges. The proposed LNMS lung segmentation method effectively distinguished lung edges and removed background interference. The Inf-Seg-Net model, which combines effective segmentation, rapid learning, and better training results, proved to be a promising approach for identifying infections using lung segmentation. The performance of Inf-Seg-Net was then compared with that of recent CNN systems, namely UNet, SegNet, and ResNet. The results demonstrate that Inf-Seg-Net outperformed the existing models, surpassing UNet, SegNet, and ResNet in infection segmentation accuracy by 0.2%, 31.56%, and 24.5%, respectively. In comparison, ResNet and SegNet performed worse than Inf-SegNet and UNet. Future studies could focus on identifying the severity of COVID-19 infection using similar AI-based techniques, building upon the successes of the proposed Inf-Seg-Net model.

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Conflicts of interest
The authors have no conflicts of interest to declare.

Author's contribution statements
J. Kalaivani: Study's design, data collection, analysis, comprehensive literature review, performed data analysis, writing, and revision, ensuring accuracy. **A.S. Arunachalam:** Interpretation of findings, actively participated in the writing, revision process, drafting the manuscript, organizing the content, providing feedback and suggestions for improving the paper.

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Appendix I

S. No.	Abbreviation	Description
1	AI	Artificial Intelligence
2	ASRNN	Attention Segmental Recurrent Neural Network
3	CAD	Computer-Aided Diagnostic
4	CAPA-ResUNet	Content-Aware Pre-Activated Residual UNet
5	CDF	Cumulative Distribution Function
6	CLAHEN	Contrast Limited Adaptive Histogram Equalization Based on Non-Local Mean Filter
7	CNNs	Convolutional Neural Networks
8	CT	Computed Tomography
9	CRF	Conditional Random Field
10	CXR	Chest X-ray
11	DL	Deep Learning
12	DNN	Deep Neural Network
13	FCNs	Fully Connected Networks
14	GAN	Generative Adversarial Networks
15	Inf-Seg-Net	Infection Segmentation Network
16	IoU	Intersection Over Union
17	LNMS	Logarithmic Non-Maxima Suppression
18	MCA	Multiple Component Analysis
19	MINN	Modified Inception Neural Network
20	ML	Machine Learning
21	NLM	Non-Local Means
22	R-CNN	Region-based Convolutional Neural Networks
23	RNA	Ribonucleic Acid
24	ROI	Region of Interest
25	RT-PCR	Reverse Transcription Polymerase Chain Reaction
26	SVM	Support Vector Machines
27	TQWT	Time-Variant Quaternion Wavelet Transform