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Lung Infection Detection using Progressive UNet Architecture

Ashish Pandey, Sandeep Dubey

Abstract

The fragmentation of medical images of tissue anomalies in organs or the blood vascular system is critical for any computerized diagnostic system. Nevertheless, automated segmentation in medical image analysis is complex since it requires in-depth information about the target organ architecture. This paper presents UNet, an end-to-end deep learning segmentation technique for early recognition of COVID. The proposed UNet model is progressive and capable of diagnosing different lung infection types along with COVID-19 infection. For this, computed tomography images are considered. The XGBoost classifier is integrated with UNet for feature classification in this model. The result analysis was performed on different convolution neural network models, that is, ResNet50, Inception, ResNet101, ResNet152, DenseNet, and UNet. These models were implemented on MATLAB using the deep neural network toolbox. From the result, it has been noticed that Inception achieved a minimum accuracy of 85.2%, and UNet achieved 99% of accuracy. It has been observed that UNet achieved approx. 16% of improvement over the inception model.

Keywords: Computed tomography images, COVID-19, Lung infection, Pneumonia

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Introduction

The world is currently hit by a pandemic disease called COVID-19 spread through coronavirus, which has deadly affected trillions of people worldwide. 17.5 crores confirmed cases and 37.8 lakh deaths are confirmed worldwide, whereas 2.93 crores confirmed cases and 3.63 Lakh deaths are confirmed in India. The first case was confirmed in December 2019. Over 200 countries were pushed their health system to control the pandemic and improve their health. So many preventions, experimentation, and diagnosis were attempted to prevent the disease, but the disease is still spreading deadly in India. The pandemic faces severe issues and challenges like lack of medication, unawareness, lack of proper diagnosis system, and lack of research. Hence, it gives a field in research for N number of scholars that grab a lot of attention.[1,2]

Scholars have put their effort into finding the way for the effective, rapid, and quicker diagnosis of disease by various means. The reverse transcription polymerase chain reaction test is the only way that is used widely for the diagnosis, but it also lacks the result as its false-negative cases are a potential threat to public wellness. Missing or misleading any COVID cause can significantly spread among the people and infect a large community. The first stage of Corona was not that deadliest, but with the second wave, it hits the death ratio, and a prediction of the third wave is even worse. Till now, the diagnosis of COVID-19 via computed tomography (CT) scans of images has been made based on deep learning, generative adversarial network (GAN), and segmentation.[3-5]

Very grateful to have technology includes convolution neural network (CNN), AI, and ML reforming the medical diagnosis system. Hence, CT scans and X-ray images are considered for the diagnosis of lung infection as the duration of diagnosis is also an essential factor for prevention. The study also lacks the expert and experienced suggestion of radiologists during the outbreak, and data availability for training the neural network is also lacking. Besides having so many issues and challenges, many of the algorithms and models have been deployed based on deep neural networks (DNN) that effectively perform lung segmentation, classification of lung infection in terms of pneumonia, chronic obstructive pulmonary disease (COPD), and COVID-19 along with its types.[6] FOR LITTLE RESEARCH, the CNN models trained for the above-stated algorithm are done through the COPD dataset.

Department of Computer Science and Engineering, Ram Krishna Dharmarth Foundation University, Bhopal, Madhya Pradesh, India.

Corresponding Author: Ashish Pandey, Department of Computer Science and Engineering, Ram Krishna Dharmarth Foundation University, Bhopal, Madhya Pradesh, India. E-mail: ashishbpl88@gmail.com

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In contrast, significant research has been done by collecting patients' CT images from various hospitals. Hence, real-time CT images of patients and healthy subjects are considered for the overall analysis and designing of the diagnosis system. Since the CT scans are ultimately images, image pre-processing and quality are another concern to get accurate and qualitative results. Lesion segmentation and classification are also attempted and proved beneficial in the same field. To get the exact position and location of the infection in the lungs, advanced technologies are deployed in models like GAN for automatic generation of CT realistic images; data augmentation is done to increase the dataset.[7]

Early detection of COVID is also a concern for the prevention and proper action, while the existing approaches were not fit in this context. In mind, CT scans and X-rays were considered to get the characteristic of lungs like ground-glass opacities and consolidation by harnessing non-invasive techniques. Research and studies have also considered the classification of lung infections in various lungs so that accurate and reliable results can be generated.

Related Work

Yang *et al*.[1] proposed a model for automatically identifying COVID-19 through CT images that will divide it into four segments and will be helpful for medical workers. Due to less availability of CT scans, 80% (16 cases) of slices are used for training, and the rest 20% are used for testing, and just for the same reason, data augmentation is also performed. MultiResUNet is used to deploy the algorithm. The model uses four convolution layers followed by the Rectified Linear Unit (ReLU) activation function, and the last layer uses the sigmoid activation function. Initially, the model did not achieve the expected result, so skip connection, LeakyReLU, and batch normalization is used in the encoder. This structure is called a Residual Block. Furthermore, the single loss function is insufficient for the model for clear image and pixel issues, so three functions, namely binary cross entry loss L_b, focal loss L_f and Tversky loss $L_{t,}$ are used. The proposed model has nicely segmented the four parts left and right lung, disease, and background through CT images based on computer-aided automatic segmentation based on deep learning. Future work involves a dice similarity coefficient, more precision, and a more extensive database.

Zheng *et al*.[2] proposed a multi-scale discriminative network (MSD-Net) for multi-class segmentation of COVID-19 CT images to detect infection in the lungs. The paper proposed a biased segmentation network (MSD-Net) that can perform multi-class infection segmentation. Data were collected from the hospital affiliated with Qingdao University, including reports of both non-COVID and COVID patients, including 20 women and 16 men of different age groups. The CT infection categories are ground-glass opacities, interstitial infiltrates, and consolidation according to lesions degree of symptoms and labeled by professional doctors. The experimental result showed that the three infection categories' DSC was 0.7422, 0.7384, and 0.8769 resp. The proposed model proves to be effective in segmentation CT images of lungs. It also provides a quantitative analysis method for the diagnosis of COVID-19. Moreover, the author has used the idea of a Pyramid Convolution block to achieve the multi-scale receptive fields of input feature maps.

Abdar *et al*.[3] presented a model based on a deep learning CNN to classify COVID-19 positive patients from a non-infected person via CT images of the chest. To test and train the model, 10,979 Ct images were used from 131 COVID-positive patients and 150 COVID-negative patients. The model is implemented using popular network VGG16 due to its less complicated, three dense layers, ReLU as activation function was used, and Adam optimization is applied. The dataset is divided into three groups training, validation, and testing. The author has divided the dataset into three categories 16% for validation, 20% for the test, and the remaining 64% is used for training. The model also performs image pre-processing so that it has accurate and better results. Experimental results show 90% accuracy in classifying CT scan images into infected and non-infected ones. The model lacks in the dataset because of non-availability, and it can be improved further employing the GANs. More feature selection can be input to get the improved and better model of the same.

Wang *et al*.[4] proposed a model based on Deep learning for the automatic diagnosis of COVID-19 on chest CT. The model's name is Weakly-supervised lesion localization which uses a combination of unsupervised lung segmentation along with activation region produced by a DNN. The model uses the segmented lung region done by pre-trained UNet, which is then fed into a DNN to predict the probability of infection. Several layers were used in the form of stages. The first stage consists of vanilla 3D convolution, a batch norm, and a pooling layer. The second stage consists of two residual blocks. The third stage consists of a progressive classifier with three 3D convolution layers. The softmax activation function is used, and to calculate the loss, a binary cross-entropy loss function is applied in the model. Data augmentation and image pre-processing are done before the model input to improve the appearance and data quality. A total of 630 CT scans were collected for preparing the dataset, among which 499 were used for training, and the rest 131 were used for the test. Experimental results achieve 0.959 ROC AUC and 0.976 PR AUC on a 0.5 threshold value. The model obtained excellent results in achieving the result for classification and good lesion localization results. The author concludes that clinical staff can use the model to diagnose COVD-19.

Pei *et al*.[5] proposed a multi-point supervision network (MPS-Net) to segment lung CT images. A multi-scale feature extraction structure, a sieve connection structure (SC), a multi-scale input structure, and a multi-point supervised training structure were implemented into MPS-Net. To increase the ability to segment various lesion areas of different sizes, the multi-scale feature extraction structure and the SC will use different sizes of receptive fields to extract feature maps of multiple scales. The inception model used in the algorithm increases the depth and width of a network. The model uses ReLU and batch normalization as activation functions. The SC module replaces the original skip connection layer in the UNet network. The model uses encrypting decrypting module in which the encoder is used for feature extraction at the input side, and the decoder is used at the output side. The overall loss is calculated through the Tversky loss function. The experimental result achieves 0.8325, 0.8406, 0.9988, and 0.742 values for DSC index, Sens index, Spec index, and IOU index, respectively. The author states that the proposed algorithm can effectively segment the CT images of patients showing infected lesions.

Fan *et al*.[6] proposed an automated deep learning approach for detection. The paper presents a network, namely, Inf-Net, for automatically identifying infected regions through CT images of the chest since lesion segmentation faces numerous issues and challenges. It utilizes implicit reverse attention and explicit edge attention to enhance the recognition of infected regions in CT images. Several convolution layers are used for pre-processing edge attention modules. The maps generated by these input layers are fed into the sigmoid activation function are used for prediction. The loss of the implementation is calculated by loss function $L_{edge,}$ an aggregate of weighted IoU loss function, and weighted binary class entropy for each segmentation. The paper concludes with an effective segmentation of CT images via the proposed model. The system has great potential and can be used in the detection of CORONA that the proposed model can detect the objects with low-intensity contrast between infections and normal tissues.

Wang *et al*.[7] proposed a rapid screening framework that predicts whether a CT scan image contains pneumonia. It also identifies its types as COVID-19 or ILD. In a framework, two 3D- ResNets are combined to perform detection of pneumonia and its type respectively by designing a prior-attention residual learning block. Paper states it's easy to deploy a model with 100 layers, so a proper hierarchy is applied to achieve the result. Each model layer is followed by batch normalization and ReLU as an activation function. Sigmoid activation is used, and for calculating loss cross-entropy, binary type classification is combined. Total 251 chest CT images were available, among which 51 were pneumonia-free, and the rest were pneumonia infected, whereas the testing dataset contains 600 scans.

Wang *et al*.[8] attempted an approach to establish a way to segment the lungs CT. The paper proposes a model based on deep learning neural network for segmentation of chest CT. The dataset is prepared from the reports of Germany and China, which consist of 165,667 CT images of the chest. The feature variation block used in CNN effectively enhances feature representation potential. The proposed method is named COVID SegNet. The network consists of two parts encoder and decoder. The encoder has four convolution layers, and the decoder has three layers. Atrous spatial pyramid pooling is chosen with different dilation rates to increase receptive field size. The feature variation block and ASPP progressive blocks effectively highlight the boundary and position of COVID-19. Sigmoid activation is used, and the total loss is calculated by combining dice loss and cross-entropy loss. The experimental result achieves Dice similarity coefficients are 0.987 and 0.726 for lung and COVID-19 segmentation, respectively. The model can segment the CT images for the diagnosis of COVID-19.

Hanseok Ko *et al*.[9] proposed deep learning-based computer vision methods with a GAN that can adaptively generate high-quality realistic COVID-19 CT images. This GAN-based COVID 19 method includes two types of infection ground-glass opacity and consolidation. A global-local generator learns the feature from CT lungs images, and a multi-resolution discriminator is employed for balancing the local details. The data augmented segmented images are taken as input to the generator. The dual discriminator approach is used to effectively learn the local information, ultimately giving a better result. A weighted network of three convolution layers and two fully-connected layers is trained, and ReLU is employed as an activation function. The model has designed loss function as cGAN loss function by two major losses. The first one is the loss for GAN and the second for the dynamic feature matching. 829 CT images were taken in the dataset, out of which 73 were used for training, 73 for semantic segmentation, and 300 for the test set. The proposed experimentally shows that it can effectively generate realistic COVID CT images. The evaluation results for semantic segmentation performance demonstrated that the high image quality and fidelity of the synthetic CT images enable their use in image synthesis for COVID-19 diagnosis using AI models. For future research, the authors plan to fully utilize high-quality synthetic COVID-19 CT images to improve specific computer vision approaches that can help in the fight against COVID-19, such as lung CT image semantic segmentation and rapid lung CT image-based COVID-19 diagnosis

Xie *et al*.[10] proposed a relational approach that leverages structured relationships. In the paper, two data sources, COPD and COVID-19, were taken from 5000 total subjects of COPD, out of which 4000 were used for training and 1000 for testing and a total of 470 subjects of COVID CT images out of which 370 for training and the remaining 100 used for testing. Two cascaded CNN were employed for lobe segmentation. Features extracted from the input are batch normalized and activated through ReLU. The sigmoid activation function is also applied for single-channel probability maps. The final is a summation of four terms. Each is a generalized dice loss which is then aggregated into K cross-entropy to calculate the final loss of the model. The idea of capturing visual and geometric correspondence proves beneficial in representing structured relationships. The proposed algorithm RTSU-Net outperforms the segmentation of lobes so accurately with small dataset availability as it precisely generates the boundaries of CT scans. Lobe segmentation is crucial to get the exact details of lung damage, especially in cases like COVID. The proposed model gives a better result and concludes with a hypothesis that the algorithm's performance is improved with the larger dataset. Furthermore, the authors have publicly shared their algorithm for lobe segmentation so that more analysis and interpretation can be made for future research.

El-Kenawy *et al*.[11] proposed a classification method with two stages to classify different cases from the chest X-ray (CXR) images based on a proposed Advanced Squirrel Search Optimization Algorithm (ASSOA). The first stage is the feature learning and extraction processes based on a CNN model named ResNet-50 with image augmentation and dropout processes. The ASSOA algorithm is then applied to the extracted features for the feature selection process. Finally, the multi-layer perceptron neural network's connection weights are optimized by the proposed ASSOA algorithm (using the selected features) to classify input cases. A Kaggle CXR images (Pneumonia) dataset consisting of 5863 X-rays is employed in the experiments. The sigmoid function is used as an activation function. The proposed algorithm achieved a mean accuracy of 99.26% and an AUC value equal to (0.9875 to classify the new input. The validation of the experiment is done through the Wilcoxon rank-sum and analysis of variance test.

Wu *et al*.[12] proposed a combined approach towards identification and segmentation. The author deployed a joint system of Novel joint classification and segmentation (JCS) that performs real-time CT diagnosis for COVID 19. The paper proposed a system for diagnosis and a dataset for COVID-19 named COVID-CS, which includes 144,167 CT images comprising 400 COVID-19 patients and 350 uninfected cases. 3855 chest CT images of 200 patients are annotated with fine-grained pixel-level labels of opacifications. The model consists of two branches that uniquely identify the COVID 19 opacification and a segmentation branch to discover the opacification area. One branch diagnoses via classification and another one through activation mapping techniques. Various activation mapping techniques are considered, and to calculate the losses among these versatile methods, several loss functions are applied such as cross-entropy, dice loss, and segmentation loss. For the segmentation task, the training set contains 2794 images from 150 COVID-19 patients, and the test set has 1061 images from the other 50 COVID-19 cases. The training set includes the 2794 images from the 150 COVID-19 infected cases in the segmentation set for the classification task.

Moreover, a random pick of 150 uninfected cases with 7500 CT images as negative cases for training has been taken. The test set contains the 64,711 images of the other randomly selected 200 infected cases and the 68,041 images from 200 uninfected subjects. The model JCS presented in the paper effectively identifies the suspected patient if the patient is positive or negative. The model achieved 95.0% sensitivity and 93.0% specificity on the classification test set of the COVID-CS dataset. In comparison with other state-of-the-art, the proposed model gives a better result. Furthermore, segmentation is improved by 8.8% on the dice matrix.

In the literature mentioned above discussions, some significant points are identified that are beneficial for the research

Table 1: Recent contributions of researchers

Reference	*Method*	*Infection Type*	*Limitations*
[1]	ResUnet	Covid-19	• The model was dedicated to identifying only Covid-19 infections • The average precision of disease was quite low (~72%) • Dice Similarity score was also low
[2]	ResNet	Covid-19	• Mild symptoms were difficult to identify
[3]	VGG16	Covid-19	• With the increased data size, there is a need to change the network architecture • The precision rate was low
[4]	ResNet	Covid-19	• With increased threshold of infection the accuracy rate decreases and increased false rate
[5]	MSD-Net	COVID-19	• Lower sensitivity and dice scores are also low
[6]	Inf-Net	Lung infection	• Lower sensitivity and dice score is also low
[7]	ResNet	COVID-19	• The model is dedicated to viral infection only
[8]	AttentionNet	COVID-19	• The precision rate is quite low for COVID infection
[9]	GAN	COVID-19	• A low PSNR ratio was observed
[10]	RTSU-Net	Lung infection	• Low accuracy of segmentation
[12]	JCS	COVID-19	• The segmentation test failed on some images and achieved a low dice score

perspective. These are highlighted in Table 1.

Methodology

System Description

In this section, a deep learning approach is used in this work that is performed in the following steps, as depicted in Figure 1.

Image pre-processing

For disease diagnosis, such as lung infection detection, medical image processing includes the segmentation process as a critical step towards improving disease diagnosis, treatment planning, monitoring, and clinical trials. However, the accurate position of abnormalities segmentation is a challenging issue because of following reasons:

- First, medical images can be acquired with a wide range of protocols and usually have low contrast and inhomogeneous appearances, leading to over-segmentation, and under-segmentation
- Second, some structures have large scales and shapes, making it hard to construct a prior shape model.

Feature extraction

In this stage, the proposed CNN is presented for feature extraction and segmentation of the image.

Feature classification

In this stage, the segmented and non-segmented features are fed into the classification model for disease classification.

For the entire work, the paper presents the UNet model is adopted for the segmentation and classification of lung infection because the model is composed of encoding and decoding layers that preserve the spatial information among layers.[13] Compared to a fully connected network, the proposed model can localize and learn patterns more effectively.

Network Architecture Description

This image classification model employs the UNet network design. This architecture is primarily intended for medical image segmentation. The UNet architectural style is a fully CNN from start

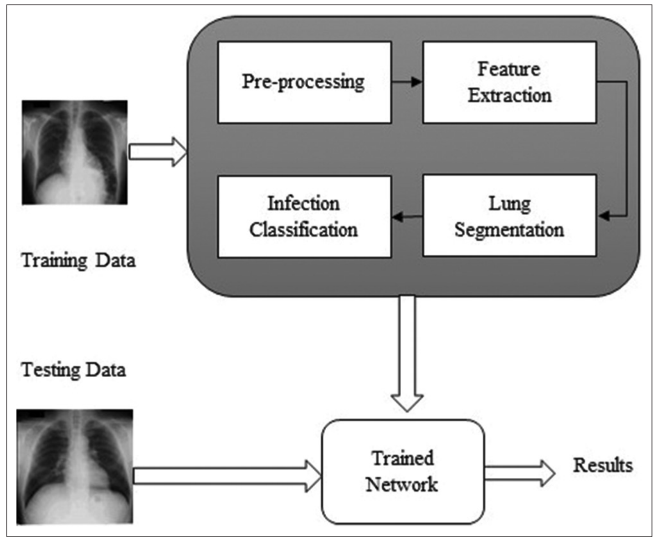

Figure 1: Block diagram of proposed model

to finish. This architecture comprises two pathways: contraction path and expansion path. It appears to be a "U" shaped building. Convolution procedures were performed in the contraction route, proceeded by max-pooling methods with a stride size. The transposition convolution operation must be performed in the expansion route. The UNet design is made up of two 3 × 3 convolutions, accompanied by a ReLu and 2 × 2 max-pooling procedures with a stride of 2 for the sub-sampling path. In the upsampling path, a 2 × 2 inverted convolution operation was performed to reduce the characteristic streams. Convolution route Skip connections are another feature of the UNet design. This link is utilized to restore the spatial characteristic dropped throughout down sampling procedures by skipping characteristics from the contracting path to the expanding path. Compared to other segmentation techniques, the segmentation is thus highly quick and precise. This design has convolutional, pooling, and up-ampling layers. Rather than Tanh, logistic, arctan, or Sigmoid as activation functions, it employs the ReLU function that reduces the chance of a fading gradients issue. It is comparatively faster than that of other hierarchical designs.

The UNet architecture is a well-known CNN structure for clinical image segmentation. The UNet architecture supports both supervised and unsupervised learning techniques. Images of various sizes are fed into the UNet architecture that quickly creates high-resolution photos from fuzzy images. UNet is an encoder-decoder network design that spans the whole network. The encoder component of the UNet design learns low-level characteristics, whereas the decoder component acquires high-level characteristics from the encoder components. Skip connections are also employed to combine the encoder and decoder path characteristics. This concatenation process enables extensive network monitoring. As a result, the classification of medical images using the U-Net architecture is exact.

Convolution that is dilated Instead of employing consecutive pooling layers, dilated convolution or atrous convolution is motivated by wavelet transform, which might also construct multi-scale contextual information. It regulates the interpretation of such data by progressively expanding the receptivity field of filters. Assume that F [x] is a discrete input and W[x] is a discrete filter or kernel. The typical spatial convolution may be calculated as follows:

$$F\left[x\right]*W\left[x\right]=\sum_{k=-\infty}^{+\infty}F\left[k\right]\bullet W[x-k], \tag{i}$$

Where "*" and "·" denote convolution and standard multiple, respectively, the dilated convolution with dilation rate R is therefore specifically defined:

$$F\left[x\right]*_{R}W\left[x\right]=\sum_{k=-\infty}^{+\infty}F\left[k\right]\bullet W\left[R\left(x-k\right)\right] \tag{ii}$$

It is worth noting that as the dilation rate is raised, the resultant receptive field increases exponentially. This relationship may be written as $(2^{(R+1)}-1) \times (2^{(R+1)}-1)$, and it is equal to conventional convolution when R = 1. Therefore, where the amount of learning variables rises continuously, dilated convolution might regulate the interpretation of relevant information.

Pyramid Pooling Module (PPM) - The (PPM primary)'s function is to produce ensembles high dimensional maps that reflect worldwide relevant information at many levels. In contrast to the SPP, which feeds fattened and concatenated multi-level data into a fully CNN in classification tasks, PPM might decrease information loss across sub-levels and achieve worldwide productivity presentations. The PPM begins with samples that were diluted the convolution features into four parallel processing levels of varying sizes. Higher pooling factors yield coarse characteristics, and lower pooling elements yield finer depictions.

Then, the constriction layer, which employs 1 1 convolution, is implemented correctly after each pooled characteristic to enhance computing capabilities by decreasing the contextual dimension to 1/n, where n is the tier size of the hierarchy.

Before pyramid pooling, every pyramid tier is up-sampled using bilinear interpolation to return to its original feature space. Finally, all of the up-sampled extracted features are concatenated with the initial feature map to merge global context characteristics. For example, if the pooling pyramid's tier size $n = 4$, the local features of each level will be decreased by a factor of 1/4.

Proposed U-Net Architecture - The U-Net structure is a variant of the fully convolutional networks commonly used for semantic segmentation. U-Nets are superior to traditional CNNs since they can give localized and classified outcomes. Moreover, it is more beneficial than Fully Convolution Networks as U-Nets can operate with fewer training images while producing more exact subsets. Throughout this situation, allocation involves labeling each image pixel in an image with a specific category. This is accomplished by constructing upsampling layers with a huge set of feature channels that allow reference images to be propagated to better resolution levels. The U-contracting Net's route is standard CNN design, comprising of repeated 3 × 3 convolutions and max-pooling procedures with stride 2 for down-sampling. These down-sampling procedures double its set of feature channels before up-sampling the feature map and performing a 2 × 2 convolution on the expanding route. These procedures cut the number of feature channels in half before concatenating them with the trimmed feature map from the contracting path. Then, an extra convolution layer is added to transfer every feature vector to the required class labels. The U-Net can collect image background by employing the contracting path, but the symmetrical expanding path allows for accurate localization. By integrating the high definition characteristics from the contracting pathway with the up-sampled result, localization is accomplished. The model's up-sampling section also includes many characteristic channels, which enable the network to transfer contextual data to high-definition resolution layers.

The UNet proposed framework is used in this image categorization model. This design is solely intended for medical image processing. The UNet contemporary design is a fully CNN from the start until the end. This design consists of two paths: contraction path and expansion path. It looks to be a "U" shaped structure. Convolution operations were run in the contraction pathway, followed by max-pooling with a stride size. The expansion route must be used for the transposed convolution process. Below Figure 2 depicts the schematic for this architecture. The network's contracting route comprises repeated 3 × 3 convolutions, a ReLU, and a 2 × 2 max pooling operation with stride 2 for down-sampling. Every stage of the down = sampling process doubles the number of features, which are subsequently halved in the expanding route. This is accomplished by upsampling, 2 × 2 convolutions, and concatenating the result with the appropriate feature mapping from the contracting pathway. The last layer maps the feature representation to the class labels, and that's one for the classification model, using a 1 × 1 convolution.

XG- BOOST - XGBoost is a newly dominant method in applied machine learning and Kaggle contests for organized or tabulated information. XGBoost is a gradient-boosted decision tree application designed for speed and reliability. Gradient boosting is so named because it employs a gradient descent technique to minimize loss when adding a new model. The weak learners are regression trees whenever gradient boosting is used for regression. Still, every regression tree translates an incoming data item to one of its leaves, which carries a consistent score. XGBoost reduces a systemized objective function that incorporates a convex loss function and a model complexity punishment component (in other words, the regression tree functions). Iterative training is used to build new trees that forecast the residuals or mistakes of previous trees, which are then merged with the previous trees to produce the desired prediction. XGBoost may be used to execute bespoke training programs that can integrate extra data analysis into the training tasks.

Networking Training - The twofold cross-validation technique is used to train networks. The basic task of twofold cross-validation is to provide a dynamic and eliminate any bias technique during model construction. This is achieved by separating the data into three subsets: training, validation, and testing. The predicted

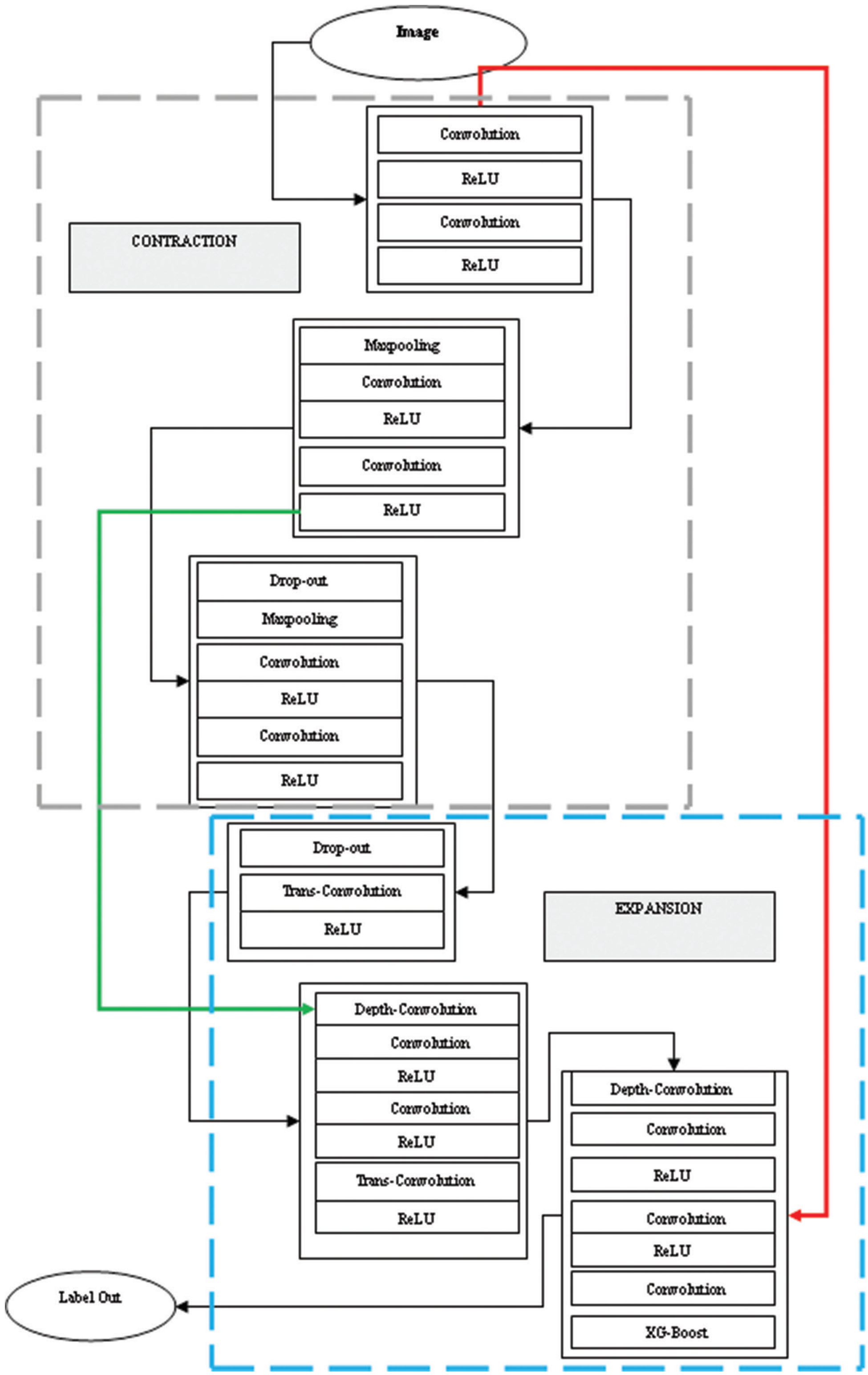

Figure 2: Proposed progressive UNET architecture

inaccuracy among segmented maps and ground-truth annotation is calculated using the dicing loss function (L_f), as per eqn (iii):

$$L_f = 1 - \frac{2 \times (sm \cap gt)}{sm \cup gt} \quad \text{(iii)}$$

The testing set is used for topology control, whereas the testing set is used for model assessment. Forward and backward propagating phases occur during network training, resulting in the computation of predictions mappings and predicted segmentation faults. Forward and backward propagating phases occur throughout the training phase, resulting in predictions maps and calculated segmentation errors.

Data Description

In this paper a mixture of two datasets is used: 85 Japanese Society of Radiological Technology examples of standard CXR images (4020 × 4892 pixels) (JSRT). CXR images comprise 107 and 10 COVID-19 and SARS samples, respectively, with (4248 × 3480 pixels).

Implementation Details and Results

To produce additional samples, various pre-processing techniques such as flipping up/down and right/left, translations, and rotating at randomized five various angles are used. The database was then categorized into 70% for training the model and 30% for assessing the classifier's performance. To retrieve racist and discriminatory characteristics from the original categories, a UNet pre-trained network is proposed in the deep learning method for the category breakdown layer. All of the investigations in this research were run in MATLAB 2019a. In this part, an empirical investigation of the relationships for lung infection detection using CNN is carried out. Lung infections are categorized as either normal, bacterial, viral, or COVID-19 illnesses. Figure 3 shows various X-ray images of lung infection for this purpose. This section outlines certain significant achievements made when using CNN for infection detection. Extraction of features from pre-processed data leads to more efficient and robust analysis. Another issue is that unbalanced data size causes training difficulties for Convolutional networks, while large image data sizes cause challenges to find during training. The result analysis was compared with various ImageNet pre-trained CNN networks in the transfer learning stage of UNet, including ResNet50,[14] Inception,[15] ResNet101, ResNet152,[16] and DenseNet.[17] Table 2 compares their effectiveness, and Figure 4 below compares their accuracy.

The accuracy is evaluated as eqn (iv):

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad \text{(iv)}$$

Where, TP = True Positive, TN = True Negative, FP = False Positive and FN = False Negative

In this research, progressive UNet, a deep CNN, is proposed to cope with abnormalities in a COVID-19 database using the benefits of class segmentation inside CNNs for image classification. UNet is

Table 2: Performance comparison of exiting CNN models for lung infection detection

CNN Models	*Accuracy (in %)*
ResNet50[14]	95.38
Inception[15]	85.2
ResNet101[16]	96
ResNet152[16]	94
DenseNet[17]	98
Ours	99

CNN: Convolution neural network

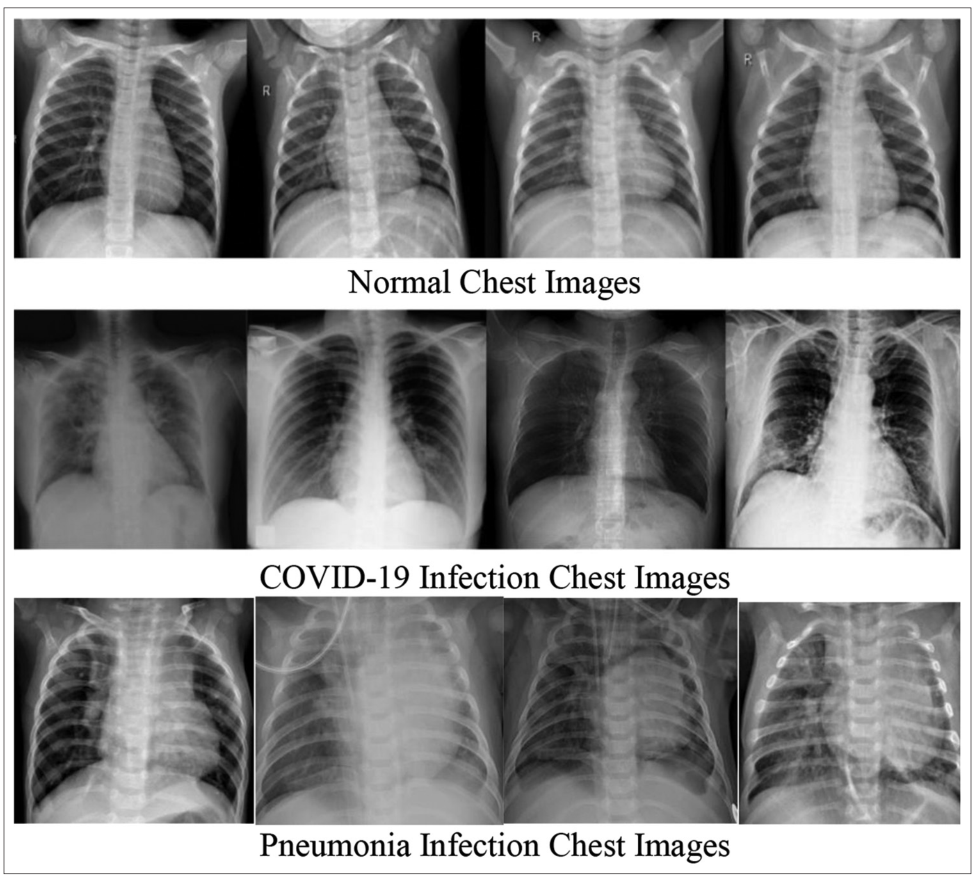

Figure 3: Samples of chest X-ray images for normal and different lung infections

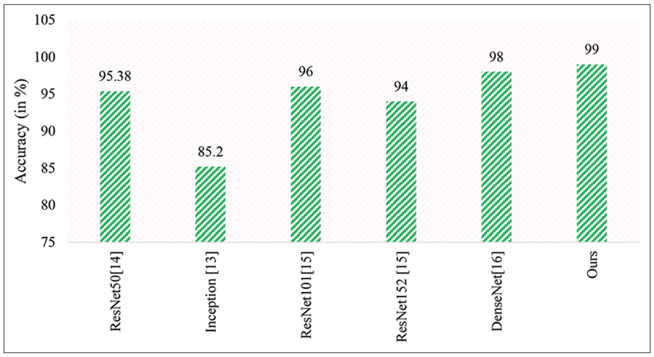

Figure 4: Performance comparison of exiting convolution neural network models for lung infection detection

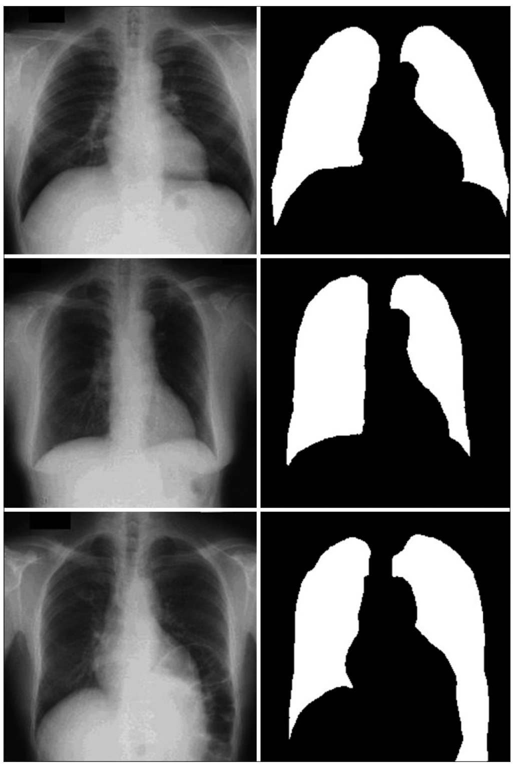

Figure 5: Infected lung segmentation result of proposed model

a general transfer learning model designed to transfer information from a large-scale object recognition challenge to a domain-specific one. In this research, the proposed progressive UNet had verified its efficiency compared to those mentioned above different CNN models using a COVID-19 dataset with imbalanced classes. Some samples of segmentation of lung infection are presented in Figure 5. The graphical representation shown below in Figure 4 depicts the accuracy of all the models that are used during the training phase.

UNet has achieved the highest accuracy of 99% compared with ResNet50, Inception, ResNet101, ResNet152, DenseNet, and UNet. At the same time, Inception achieved a minimum accuracy of 85.2% compared with other CNN Models. While ResNet150, ResNet152, and ResNet101 attain average accuracy of 95% and after UNet, only DenseNet is the CNN model, which acquires 98% accuracy.

Conclusion

Coronavirus symptoms are often related to pneumonia, which can be detected by chromosomal and imaging testing. The envision test can enable rapid identification of COVID-19 and help stop the spread of the illness. X-ray and CT imaging methods have shown good efficiency in detecting COVID-19 disease. Because of the increasing availability of labeled image datasets, significant progress has been achieved in deep CNNs for medical image processing. CNN's allow for direct instruction of deep, genuine, and structured local feature representation from the information. This paper presents a progressive UNet architecture to categorize COVID-19 images in a large dataset of CXR images. The result was evaluated on the model's accuracy and compared with some existing CNN models such as ResNet, Inception, and Densenet. The proposed progressive UNet achieved 99% accuracy and demonstrated excellent and robust solutions for COVID-19 case categorization and its capacity to deal with data inconsistency and a limited set of training images. This work will be extended on low contrast and noisy images in the future.

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