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Lung Infection Detection using Progressive U-NET Architecture

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Abstract

The fragmentation of medical images of tissue anomalies, imorgans, or the blood vascular system is critical for any computerized diagnostic system. Nevertheless, automated categorization in clinical visual assessment was a difficult problem as it necessitates in-depth information about the specific organ structure. This article presents UNET, an edge deep learning categorization technique for early recognition of COVID. This is also a problem for treatment and correct intervention, as previous techniques were inappropriate in this situation. Trying to keep this in consideration, non-invasive methods such as CT scans and X-rays were suggested to get characteristics of lungs.

Keywords: Lung Infection, Pneumonia, COVID-19, CT images.

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Introduction

A global current disease named COVID-19 spread via corona virus has deadly affected trillions of people worldwide till now. Till now, 17.5 crore confirmed cases and 37.8 lakh deaths are confirmed worldwide whereas 2.93 crore confirmed cases and 3.63 Lakh deaths are confirmed in India. First case was confirmed in December 2019. Over 200 countries were pushed their health system to control the pandemic and improve the health. So many prevention, experimentation, and diagnosis were attempted to control the disease, but even still the diseases is yet 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. So, it gives a field in research for N number of scholars that grab a lot of attention.[1,2]

Scholars have put their effort in finding a way for the effective, rapid and quicker diagnosis of disease by various means. The RT-PCR test is the only way at current used widely for the diagnosis but also lacks in terms of result. As its false-negative cases are a possible hazard to population health. Lost or mislead of any COVID cause can lead to a major spread among the people and can infect a large community of people. The first stage of Corona was not that much deadliest but with the second wave it hits the death ratio and a prediction of third wave is even worse. Till now as for detection of COVID-19 through CT scans of images has been done based on deep learning, GAN and segmentation.[3-5]

Very grateful to have technology like CNN, AI and ML that are reforming the medical diagnosis system. So, CT scan and X-ray images are considered for diagnosis of lung infection as the duration of diagnosis is also an important 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 network that are effectively performing segmentation of lungs, and classification of lung infection in terms of pneumonia, COPD and COVID 19 along with its types.[6] The CNN models trained for the above stated algorithm are done via COPD dataset for little research while major research has been done via collecting CT images of patients from various hospitals. So 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 of images is one another concern to get the accurateand qualitative result. Lesion segmentation and classification is also attempted and proved to be beneficiary in the same

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field. To get the exact position and location of the infection in lungs advance technologies are deployed in models like generative adversarial networks 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 to be taken while the existing approaches were not fit in this context. Keeping this 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 infection in terms of various lungs infections so that accurate and reliable result can be generated.

Related Work

Yang et al.[1] proposed a model for automatic identification of COVID-19 via 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 were utilized for both training and relaxation. Only 20% of the total is being employed for assessment. Same reason data augmentation is also performed. MultiResUNet is used to deploy the algorithm. The model uses 4 convolution layer followed by ReLU activation function and the last layer uses sigmoid activation function. Initially the model was not achieving the expected result so skip connection along with LeakyReLU and batch normalization is used in encoder. This structure is called as Residual Block. Also, for clear image and pixel issues, single loss function is not sufficient for the model, so three functions, namely binary cross entry loss Lb, focal loss Lf and Tversky loss Lt, are used.The proposed model has nicely done the segmentation in four parts left and right lung, disease and background via CT images based on computer aided automatic segmentation based on deep learning. The future work involves dice similarity coefficient, more precision, and a larger database.

Zheng et al.[2] proposed multi-scale discriminative network (MSD-Net) for multi-class segmentation of COVID-19 CT images for the detection of infection in lungs. The paper proposedMSD-Net is a racist and discriminatory segmented network that can segment several-class infections. Information was gathered at a hospital linked with Qingado University, including reports via 20 women and 16 men of various ages, including non-COVID and COVID patients. In addition, the author applied using Pyramid Convolution Block (PCB) concept to accquire various-scale receptive areas in input characteristic layouts. As per the severity of the illness, the CT infection classifications are subsurface opacities, interstitial invades, and consolidation, which are labeled by expert doctors. To effectively boost the classification outcomes, we included the pyramid inversion block and designed an attentive block in the suggested MSD-Net.. Experimental result showed the DSC of three infection categories were 0.7422, 0.7384, 0.8769 resp. The proposed model proves to be an effective model in the segmentation of CT images of lungs. It also gives way for diagnosing COVID-19 via statistical analyses. Abdaret al. [3] presented a model based on deep learning convolution neural network (CNN) for the classification of COVID-19 positive patients from non-infected person via CT images of chest. To test and train the model 10979 Ct images were used from 131 COVID positive patients and 150 COVID negative patients. The model is implemented by using popular network VGG16 due to its less complication, three dense layers and ReLU as activation function were used and Adam optimization is applied. The dataset is divided into 3 groups training, validation and testing. The author has divided the dataset into three categories 16% for validation, 20% for test and remaining 64% is used for training. The model also performs image pre-processing so that have accurate and better results. Experimental results show 90% accuracy in classification of CT scan images into infected and non-infected one. The model lacks in dataset because of non-availability and it can be improved further by means of generative adversarial network (GANs) and 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 uses the segmented lung region done by pre-trained UNet, which is then fed into Deep neural network to predict the probability of infection. The model's named as Weakly-supervised lesion localization which uses a combination of unsupervised lung segmentation along with activation region produced by deep neural network. Several layers were used in from of stages. First stage consists of vanilla 3D convolution, a batchnorm and a pooling layer, the second stage consists of two residual blocks and the third stage consist of the progressive classifier with three 3D convolution layer. Softmax activation function is used to calculate the loss binary cross entropy loss function applied in the model. To improve the image and data quality, data augmentation and image pre-processing are done before the model input. Total of 630 CT scans were collected to prepare the dataset, among which 499 are utilized for training and relaxation. The number 131 is employed for testing.. Experimental results achieve 0.959 ROC AUC and 0.976 PR AUC on 0.5 threshold value. The model obtained great result in achieving the result for classification and good lesion localization results and author concludes that the model can be used by clinical staff for the diagnosis of COVD-19.

Pei et al.[5] presented a various supervised network (MPS-Net) for lung CT picture classification. MPS-Net includes architectures such as a several-scale feature extracted mechanism, a sieve connecting framework (SC), an inter input layout, and a multi-point guided training framework. The inter-scale extracting features framework and the sieve connecting mechanism will be using various sizes of receptive sectors to derive pattern layouts of different scales in terms of improving the capacity to segregate multiple lesion areas of varying sizes. The inception model used in the algorithm increases the depth and width of a network. The model uses ReLU and batch normalization as activation function. The sieve connection module is used to replace the original skip connection layer in UNet network. The model uses encrypting decrypting module in which encoder is used for feature extraction at input side and decoder is used at the output side. The overall loss is calculated by means of Tversky loss function. 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 suggested method can efficiently segment the CT images of patients showing infected lesions.

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

Wang et al.[7] proposed a framework for rapid screening that predict whether or not 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 pneumonia and its type respectively by designing a prior-attention residual learning block (PARL). Paper states its easy to deploy model with 100 of layers, so a proper hierarchy is applied in the model to achieve the result. Each layer of the model is followed by batch normalization and ReLU as activation function. Total 251 chest CT images were available among which 51 were pneumonia free and rest were pneumonia infected, whereas testing dataset contains a total of 600 scans. Sigmoid activation is used and for calculation of loss cross entropy, binary type-classification are combined. Moreover, for computing loss y_i^{det} is set to 0 for normal images and 1 to infected images. Further, for identifying its type three values 0,1 and 2 is chosen for Non-Pneumonic, ILD and COVID 19 infected. Results are better in compare to cutting-edge techniques. The paper concludes that the lesions located by this method are more accurate and effective as compared to other. Future work includes detection of COVID 19 in its early stages so that essentials can be done by clinical experts.

Wang et al.[8] attempted an approach to establish a way that can segment the lungs CT. The article suggested a framework rely on deep learning neural network for the segmentation of chest CT. The dataset is prepared from the reports of Germany and China which consist of 1,65,667 CT images of chest. The feature variation block used in CNN enhances the potential of feature representation effectively. The proposed method is named as COVID SegNet. The network including of two parts encoder and decoder. The encoder has 4 convolution layer and decoder has 3 layers. To increase the size of receptive field for various dilation rates, arous spatial pyramid pooling was adopted. COVID 19's border and position are effectively highlighted thanks to the characteristic modification block and ASPP successive blocks. The overall loss is estimated using sigmoid activation and a mixture of dice losses with cross entropy loss. The outcome of the operation is positive. With lung and COVID-19 categorization, the dice similarity values were 0.987 and 0.726, respectively..The model can segment the CT images for the diagnosis of COVID 19.

HK et al.[9] proposed a deep learning-based computer vision methods with generating adversarial network that also can produce high genuine COVID 19 CT pictures through an adaptive manner. 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 lung images, and a multi resolution discriminator is employed to balance the local details. The data-augmented segmented images is taken as input to generator. The dual discriminator approach is used so that the model can effectively learn the local details, ultimately giving better results. A weighted network of 3 convolution layers and 2 fully-connected layers is trained and ReLU is employed as activation function. The model has designed loss function as cGAN loss function by two main losses. The first one is the loss for GAN and second for the dynamic feature matching. 829 CT images were taken in dataset, of which 73 were used for training, 73 for semantic segmentation and 300 for test set. The proposed experimentally shows that it can effectively generate the realistic COVID CT images. The great picture quality and authenticity of such synthetic CT pictures permit their application in visual generation with COVID-19 detection utilizing AI models, according to the assessment outcomes for semantic categorization efficiency. The scientists intend to use elevated synthetic COVID-19 CT pictures in forthcoming studies to develop certain computer vision technologies that can aid in the fight over COVID-19, including lung CT visual semantic classification and quick COVID-19 identification relying on lung CT visuals

Xieet al.[10] proposed a relational approach that leverages structured relationship. In paper, two data sources COPD and COVID 19 were taken 5000 total subject of COPD out of which 4000 were used for training and 1000 for testing and total 470 subjects of COVID CT images out of which 370 for training and remaining 100 used for testing. Two cascaded CNN were employed for lobe segmentation. Feature extracted from input are batch normalized an activated through ReLU. 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 for the calculation of 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 a crucial task to get the exact details of lungs damage especially in cases like COVID. The proposed model gives better result and concludes with a hypothesis that perhaps the computation efficiency has enhanced with larger dataset. Also, Authors have publicly shared their algorithm for lobe segmentation so that more analysis and interpretation can be done for future research.

Kenawyet al.[12] proposed that relying on a hypothesized Enhanced Squirrel Browse Optimized Method, a two categorization approach was developed to categorise distinct instances from chest X-ray pictures (ASSOA). The characteristic learning as well as extracting operations, which are implemented on such a ResNet-50 Convolutional Neural Network (CNN) framework with picture enhancement and dropout techniques, are the initial stage. For the feature selection phase, the ASSOA technique is employed to the extracted characteristics. Finally, the suggested ASSOA method (using the selected characteristics) optimises the connecting weights of the MultiI-layer Perceptron (MLP) Neural Network to categorise input instances. With in trials, the Kaggle chest X-ray pictures (Pneumonia) dataset with 5,863 X-rays was used. As an activation feature, the sigmoid feature is being employed. 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 via Wilcoxon rank-sum and ANOVA test.

Wu et al.[11] proposed a combined approach towards identification and segmentation both. The paper deployed a joint system of innovative joint classification and segmentation (JCS) that execute in real time CT diagnosis for COVID 19. The paper did not only proposed a system for diagnosis but a dataset is also proposed for COVID 19 named as *COVID-CS* which includes 144167 CT images which comprise of four hundred (400) COVID-19 patients and 350 non-infected instances. A total of 3,855 chest Computed tomography pictures from 200 patients have been evaluated including fine-grained pixel-based opacification tags.. The model consists of two branch that uniquely identifies the Coronavirus or covid-19 opacification and a To find the calcifications, use the categorization branch. One branch diagnose 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 like cross entropy, Dice loss and segmentation loss. The training set includes 2,794 images out of 150 COVID-19 sick people, while the testing data includes 1,061 pictures outfrom the remaining 50 COVID-19 instances. The practice set for the segmentation problem includes 2,794 pictures across the 150 COVID-19 diagnosed instances in the segmented set.

Furthermore, 150 uninfected individuals with 7,500 CT pictures were randomly chosen as adverse instances for training. The experimental set includes 64,711 photos from 200 diagnosed instances chosen at random and 68,041 photographs from 200 uninfected instances. Whether the patient was positive or negative, this prototype JCS provided in the research efficiently detects the suspected patient. Here on COVID-CS dataset's segmentation testing set, the algorithm had 95.0 percent sensitivity and 93.0 percent specificity. The proposed model on comparison with other state-of-the-art, gives better result. Also segmentation is improved by 8.8% on dice matrix.

Methodology

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 convolutional neural network from start to finish. This architecture is made up of 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 procedures having a stride length. The transposition procedure of convolution must be performed in the extension route. The UNet design is made up of two convolutions, accompanied by a Rectified Linear Unit (ReLu) and maxpooling procedures with a stride of 2 for the sub - intance route. In the Up intance route, a 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 moving from such a shrinking to an extending route Particularly comparing to other segmentation techniques, the segmentation is thus highly quick and precise. This design has convolutional, pooling, and up-sampling 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 convolutional neural network (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 for extensive network monitoring. As a result, the classification of clinical visuals using the U-Net structure is remarkably precise.

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 expanding the receptivity field of flters progressively. 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:

$$F[x] * W[x] = \sum_{k=-\infty}^{+\infty} F[k] \cdot [W(x) - W(k)], \quad \text{(i)}$$

where '*' and '·' denote convolution and standard multiple, respectively. The dilated convolution with dilation rate R is therefore specifically mentioned:

$$F[x] * W[x] = \sum_{k=-\infty}^{+\infty} F[k] \cdot W[R(x) - R(k)]. \quad \text{(ii)}$$

It is worth noting that as the dilation rate is raised, the resultant receptive field increases exponentially. This relationship may be written as , 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 Pyramid Pooling Module (PPM primary's) function produces 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 convolutional neural network in classification tasks, PPM might decrease information loss across sub-levels and achieve productivity worldwide presentations. The PPM begins with samples diluting 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 , where n is the tier size of the hierarchy.

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

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 Convolutional Neural Networks since they can give localized as well as classified outcomes. Throughout this situation, allocation involves labeling each pixel of the image in a image with a specific category. Moreover, it is more beneficial than Fully Convolution Networks as U-Nets can operate with less training images while producing more exact subsets. This is accomplished by constructing up-sampling 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 3x3 convolutions and max pooling procedures with stride 2 for down-sampling. These down-sampling procedures double its set of function channels before up-sampling the functional layout and performing a 2x2 convolution on the extending route. These procedures cut the amount of functional streams 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 a huge number of 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. From the start until the end, the UNet contemporary design is a totally convolutional neural network. This design including of two paths: contacted route and the extended route. It looks to be a 'U' shaped architecture. Convolution functions were run in the Contraction pathway, followed by maxpooling with a stride size. The expansion route must be used for the transposed convolution process. Below Figure 1 depicts the schematic for this architecture. The network's contracting route comprises of repeated 3x3 convolutions, a rectified linear unit (ReLU), and a 2x2 max pooling operation with stride 2 for down-sampling. Every stage of the down=sampling process doubles the amount of functions, that are subsequently halved in the extending route. This is accomplished by upsampling, 2x2 convolutions, and concatenating the result with the appropriate feature mapping from the shrinking route. The last layer maps the characteristics representation to the class labels, and that's one for classification model, using a 1x1 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. XGBoost is a software library that you can install and run on your computer and afterwards interact through a range of ways. Whenever gradient boosting is used for regression, the weak learners are regression trees, but 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 previous trees to produce the desired prediction. Gradient boosting is so named because it employs a gradient descent technique to minimize loss when adding new model. XGBoost may be used as a tool to execute bespoke training programs that can integrate extra data analysis into the training tasks.

Networking Training - Here we used the twofold cross-validation technique to train networks. The basic task of twofold cross-assessment is to find the providing a dynamic and eliminate any bias technique during model construction. This is achieved by separating the training, evaluation, and testing are the three sub-categories of data.. The predicted inaccuracy among segmented maps (SM) and ground-reality annotation (GT) is calculated employing 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 throughout training phase, resulting in the computation of predictions maps and calculated segmentation errors. Forward and backward propagating phases occur during network training, resulting in the computation of predictions mappings and predicted segmentation faults.

Data Description – We employed a mixture of two datasets in this study: 85 Japanese Society of Radiological Technology examples of standard CXR images (JSRT). CXR images, that comprise 107 and 10 COVID-19 and SARS samples, respectively).

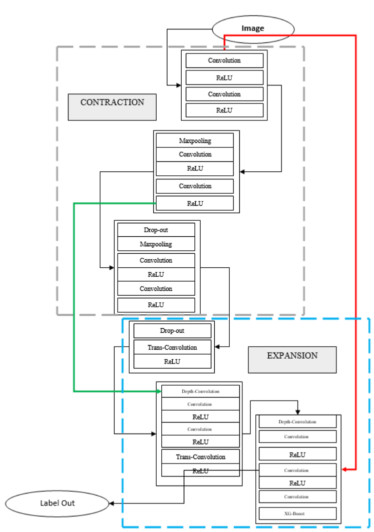

Figure 1: Proposed Progressive UNET Architecture

Implementation Details and Results

To produce additional samples, we used various preprocessing techniques such as flipping up/down and right/left, translations, and rotating at randomized five angles. The database was then categorized into 70% for training the model and 30% for assessing performance of the classifier. To retrieve racist and discriminatory characteristics from the original categories, we utilized a UNet pre-trained networks in deep learning method for the category breakdown layer. All of the investigations in this research were run in MATLAB 2019a on a computer. In this part, an empirical investigate 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 2 shows various x-ray images of a 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 challenging in finding during training. We employed various ImageNet pre-trained CNN networks in the transfer learning stage of UNET, including ResNet50 [14], Inception [13], ResNet101, and ResNet152 [15]. Table 1 compares their effectiveness, and the Figure 3 below compares their graphic efficiency.

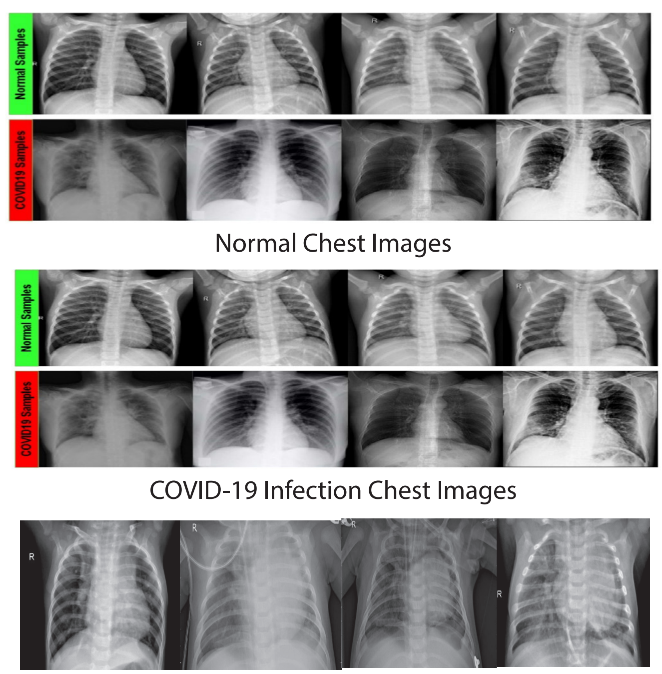

Figure 2: Samples of chest X-ray İmages for Normal and Different Lung Infections

Table 1: Performance Comparison of Exiting CNN Models for Lung Infection Detection

CNN Models	*Accuracy (in %)*
ResNet50	95.38
Inception	85.2
ResNet101	96
ResNet152	94
DenseNet	98
Ours	99

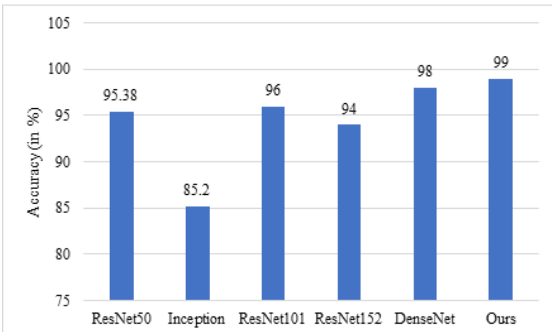

Figure 3: Performance Comparison of Exiting CNN Models for Lung Infection Detection

In this research, we modified and tested UNET, a deep convolutional neural network, to cope with abnormalities in a COVID-19 database by using the benefits of class segmentation inside CNNs for image classification. UNET is a general transfer learning model designed to transfer information from a large-scale object recognition challenge to a domain-specific one. We verified UNET and above mentioned different convolutional neural network models using a COVID-19 dataset with imbalanced classes in this research. The graphical representation shown below depicts the accuracy of all the models we used during the training phase.

UNET has achieved highest accuracy of 99% when compared with ResNet50, Inception, ResNet101, ResNet152, DenseNet, and UNet. Whereas Inception achieved minimum accuracy of 85.2% when compared with other Convolutional Neural Network Models. While ResNet150, ResNet152 and ResNet101 attain average accuracy of 95% and after UNet only Dense Net is the CNN model, which acquires 98% accuracy.

CONCLUSION

Coronavirus symptoms is often related with 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. The imaging methods X-ray and CT have shown good efficiency in the detection of COVID-19 disease. Because of the increasing availability of labeled image datasets, significant progress has been achieved in deep CNNs for medical image processing. CNNs allow for direct instruction of deep, genuine, and structured local feature representation from information. This paper presents a progressive UNet architecture for categorizing COVID-19 images in a large dataset of CXR images in this article. UNet demonstrated excellent and robust solutions for COVID-19 case categorization, as well as its capacity to deal with data inconsistency and a limited set of training images.

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