Comparative study of segmented-based and segmented-free approach for COVID-19 detection

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Abstract. According to WHO, lung infection is one of the most serious problems across the world, especially for children under five years old and older people over sixteen years old. In this study, we designed a deep learning based model to aid medical practitioner for their diagnostic process. Here, U-Net based segmentation framework is considered to get the region of interest (ROI) of the lungs area from the chest x-ray images. To detect COVID-19 disease from a collection of chest X-ray images of disparate cases in both segment-free and segmented-based lung images, a deep ensemble framework method is presented. Two standard models and a built CNN network make up this framework. For experimentation, three public datasets for segmentation and one dataset for classification were used. The performance of both the approaches returns encouraging outcome.

Keywords: Deep learning · COVID-9 · Deep ensemble · Chest X-ray · Segmentation

1 Introduction

There are many diagnostic technologies available, but X-ray is widely used, cheap, non-invasive, and easy to acquire. For diagnosing lung diseases, such as tuberculosis, lung cancer, emphysema, atelectasis, pneumothorax, and others, chest radiography is the most popular and effective imaging modality. Several fields of research have been transformed by Deep Learning techniques over the last few years [1,2,3,4]. The use of deep learning techniques is particularly beneficial in the medical field because imaging data sets, such as retinal image, chest X-ray, and brain MRI, show promising results with improved accuracy. The X-ray machines provide inexpensive and quicker results for scanning various human organs in hospitals. In most cases, X-ray images are interpreted manually by radiologist experts. Data scientists can use deep learning to train those captured images for detecting lung diseases, which will be of substantial assistance to medical experts. It will be helpful in developing countries where an X-ray facility exists, but an expert is still elusive. The convolutional neural networks (CNN) [5,6] is effective, particularly effective among various deep learning classifiers [7,9] due to its ability to handle spatial data. According to CNN results, image data can be mapped to precise and expected output with high accuracy.

Segmentation of X-ray images is necessary for better lung disease classification. It is necessary to first separate the area of interest from the entire image. Segmentation divides the image into a series of regions based on characteristics of the image that are almost constant throughout the regions. Segmenting the lungs plays an important role in developing a computer-aided diagnosis system for lung infections [8]. Automated or semi-automated image segmentation is aimed at extracting the area or region of interest (ROI) in an image. The objective of this technique is to elicit quantitative information about an organ of interest, including morphometric data. In segmentation problems, there are two related tasks to consider: object recognition and delineation [10]. The first task in this process is to determine where the object is located in the image in order to determine its position. During the object delineation task, the composition of an object is depicted to determine its character.

For cost-effective diagnosis of COVID-19, lungs images play a significant role since this disease affect lungs. Since for pneumonia and COVID-19 texture are not differentiable in naked eye which causes improper diagnostic for this reason machine learning based strategy is needed to get the enhanced performance of detection. Figure 1 represent the complete flowchart of our work. The following are the contribution of this work:

- A U-Net-based architecture is build for segmenting the ROI of lungs area for the whole chest image.
- We designed a CNN-based architecture to detect COVID-19.
- Standard deep learning framework are deployed to find out the performance.
- Deep ensemble framework was developed to get higher performance compared to the single models.
- A comparative study with state-of-the-art was performed.

2 Related works

Lasker et al [11] proposed a lightweight stacked ensemble approaches with three pretrained deep learning and a CNN network. The accuracy values of three

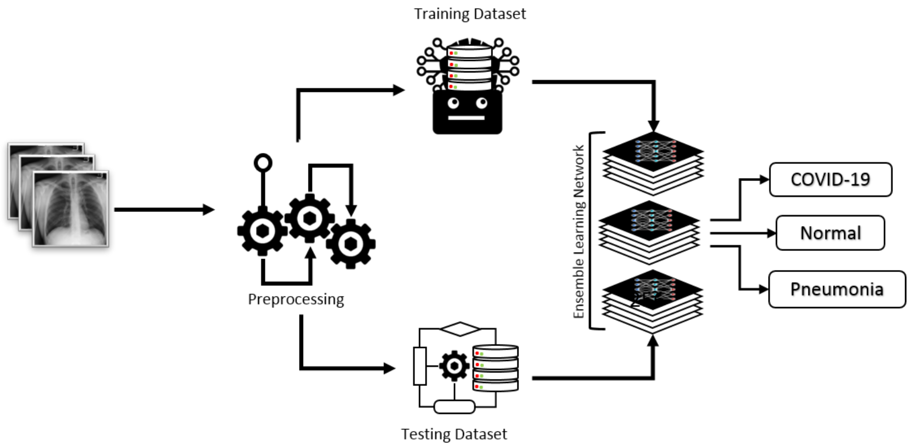

Fig. 1. Flowchart of our proposed work.

datasets are 97.28, 96.50, and 97.41 which represent the performance of the architecture implemented in three different datasets. Beside the medical imaging, Ghose et al. [22] proposed a emsemble framework for text/non-text image classification and show the improvement of classification score. Lasker et al. [19] prepared a stacked ensemble framework for lung x-ray image segmentation based on U-Net architecture. In U-Net architecture, it uses three deep learning models as a encoder: MobileNetV2, InceptionResNetV2, and EfficientNetB0. An experiment was conducted on the three public lung segmentation datasets in order to compare the proposed architecture to the conventional U-Net model. The dice coefficient was 3.02% and the IoU was 3.43%.

Chatterjee et al. [12] Proposed a class imbalance-based classification method to detect COVID-19 disease. using a variational autoencoder (VAE). They conducted extensive experimental analysis and obtained significant improvements in COVID-19 detection. Lasker et al. [18] developed deep features from DL models. The deep features were classified with the help of different traditional algorithms. The highest accuracy of the classification achieved by using MLP reached 96.81%. Gayathri et al [13] presented a method that explored comprehensive computer-aided diagnosis using the CNN, autoencoder based strategy to classify diseases.

Gour et al. [14] presented a stacked-based CNN architecture and to detect COVID-19 on radiological images. They considered discrimination attribute of the various submodels and their combination. They collected CT images to generate to prepare a dataset and accumulated X-ray images from three publicly datasets to create another X-ray image dataset. The sensitivity score for multi-class x-ray images was 97.62, and the sensitivity score for CT images was 98.31%. Authors [15,16] used a pretrained deep learning model for lungs disease detection. Author [16] get generalization feature from deep learning model. Because of bottleneck convolution, a lot of redundant information is generated during the connection process.

3 Methodology

3.1 Segmentation

We have used U-Net based architecture for segmenting lungs region. In deep learning models to get higher performance, often large number of samples are required for training but in case of U-Net architecture the performance is still good for less sample size. The U-Net segmentation approach differs from other segmentation approaches like FCN, SegNet, and DeeplabV3+ because it uses skip connections of semantic feature. In rather than transmissions of high-level semantic features in the same stage. In this way, the final recovered map will integrate more low-level features, and multiple scale features will be fused, resulting in deep supervision and multi-scale prediction.

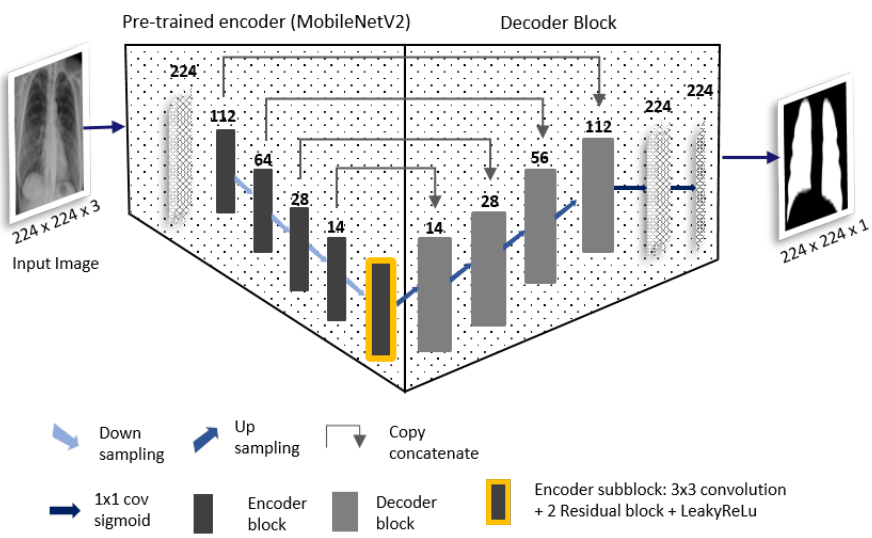

Fig. 2. Proposed U-Net architecture for segmenting lungs area..

The U-net architecture utilizes three parts, encoder, and decoder. Pretrained MobileNetV3 was used in the encoder part. This model has an input size of 224x224x3 and an output size of 224x224x1. We tested a variety of pre-training networks as the backbone, and MobileNeV2 had the most impressive results. In order to reduce pretrained architecture complexity, the value of alpha in MobileNetV2 is fixed to 0.35. The filter size of the decoder was the same as that of the encoder. A total of four filter sizes are used in the decoder block: 16, 32, 64, and 128. This pre-trained U-Net architecture depicted in the Figure 2.

3.2 Classification

C3M2D framework
We designed C3M2D (Three convolution layer, One maxpooling layer, and two dense layer) framework for segregating COVID-19 lung images from the above mention class of images. The CNN is a deep learning technique that is highly effective at segmenting, detecting, and identifying several imaging modalities in the medical field. In general in CNN there are three types of layer: convolution, pooling, and dense. In C3M2D framework, the input images with dimensions SxSxC (S and S is the row and column of the image and C denotes channel) is fed to 5x5 convolutional layers having 32 filter which is followed by two 3×3 convolutional layers with 16 mask which is fed to a 3×3 maxpool layer. Then 256, 128 dimensional fully connected layers are used which is followed by 3-dimensional dense layers for classification. This C3M2D network is presented in Figure. 3.

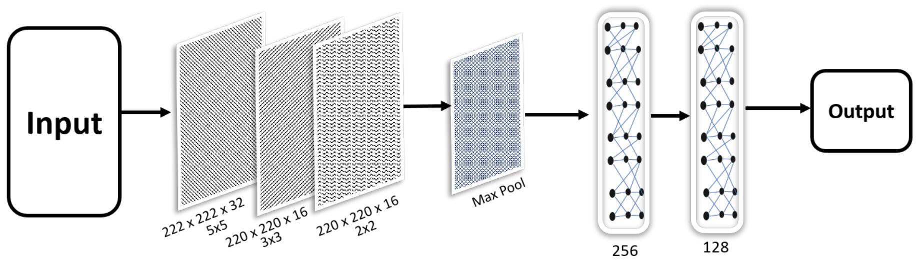

Fig. 3. The structure of C3M2D framework

Deep Ensemble Framework In order to increase classification accuracy, ensemble learning incorporates several types of classification models into one coherent system.In general, ensemble models provide a better level of robustness compared to deep learning models. This study used a horizontal voting strategy 12 to predict the final class tag by multiplying the predicted probabilities generated by the softmax functions of ResNet152, MobileNetV3, and C3M2D models. Due to the limited size of our training dataset, a horizontal voting scheme was chosen to avoid overfitting through an unstable classification error rate. The highest accuracy score is assigned to the image group that accurately identifies the disease. To represent the ensemble process, we can use the following formula.

$$F = \arg\max \prod_{k_j}^{k_i \epsilon P} k_j \tag{1}$$

In Figure 4 the proposed deep ensemble framework is depicted. In this framework, the predictions from three models are used in majority voting ensemble processed where the final prediction is obtained after multiplying of the individual prediction. Since here three models are considered, j is set to 3.

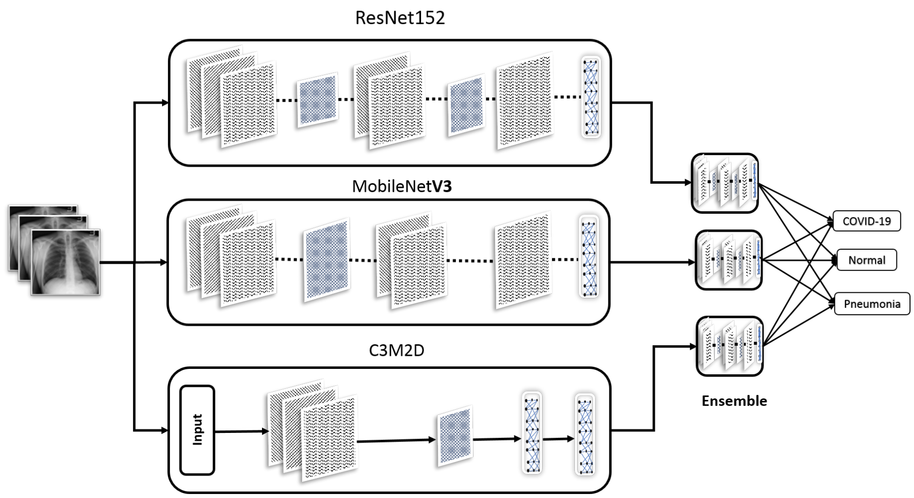

Fig. 4. Proposed deep ensemble framework for COVID-19 detection

4 Experiment

4.1 Evaluation protocols

Several performances measures are considered to assess the segmentation and classification outcomes: Dice Coefficient(DC), Intersection over Union(IoU), Accuracy, Loss, Precision, and Recall.

DC: The overlap area (A) is divided between the predicted segment(S) and the ground truth by their sum. This is expressed as follows:

$$\text{Dice Coeff} = \frac{2.A(S_{pred} \bigcap S_{g.true})}{A(S_{pred} + S_{g.true})} \tag{2}$$

IoU: The connection between ground truth and predictions is calculated using IoU metrics. It represents intersection and union ratios using labeling and predicted outcomes. Here is the formula for calculating the IoU score.

$$IoU = \frac{A(S_{pred} \bigcap S_{g.true})}{A(S_{pred} \bigcup S_{g.true})} \tag{3}$$

The True Positive rate (tp), the False Negative rate (fn), the True Negative rate (tn), and the False Positive rate (fp) are essential parameters here.

Accuracy (ACC): The accuracy of a prediction is evaluated using the following equation.

$$ACC(\varphi) = \frac{tp + tn}{tp + tn + fp + fn} \tag{4}$$

Precision: In terms of disease prediction, precision is a value that represents a positive prediction. Based on false positives and true positives, a predicted value is calculated.

$$Precision(\varphi) = \frac{tp}{tp + fp} \tag{5}$$

Recall: Using sensitivity, you can determine how many patients were detected as positive where the person was actually infected.

$$Recall(\epsilon) = \frac{tp}{tp + fn} \tag{6}$$

F1-score: Focusing on one single value as false positive or false negative may lead to overlooking another value. To combat this problem, we used the f1-score, which balances Precision and Recall.

$$f1 - score = 2(\frac{\varphi * \epsilon}{\varphi + \epsilon}) \tag{7}$$

4.2 Dataset

For image segmentation we used three benchmark public datasets Montgomery County(MC), Shenzhen Hospital(SH), and Japanese Society of Radiological Technology (JSRT) in these datasets containing 662, 138, and 247 images respectively and its corresponding mask. The MC, SH, and JSRT datasets each contain images of different resolutions, such as 4892 x 4020, 2048 x 2048, and 3000 x 3000 pixels. Training performance is improved by resizing all images to 224 x 224 dimensions to maintain homogeneity. For classification, we used RYDLS-20-v2 [21]. This dataset contains 2678 chest X-rays of three different classes.

4.3 Training Regime

To achieve better results, different hyperparameters were used in the proposed U-Net segmentation architecture. The batch size, learning rate, and number of epochs in these cases are 64, 0.0001, and 100, respectively. Figure 5 illustrates four different learning curves based on these parameters.

4.4 Results

In Table 1 performance of the proposed approach is shown using the single models and deep ensemble framework for both segmented free and segmented-based approaches. It is observed that there is a gain in accuracy using the deep

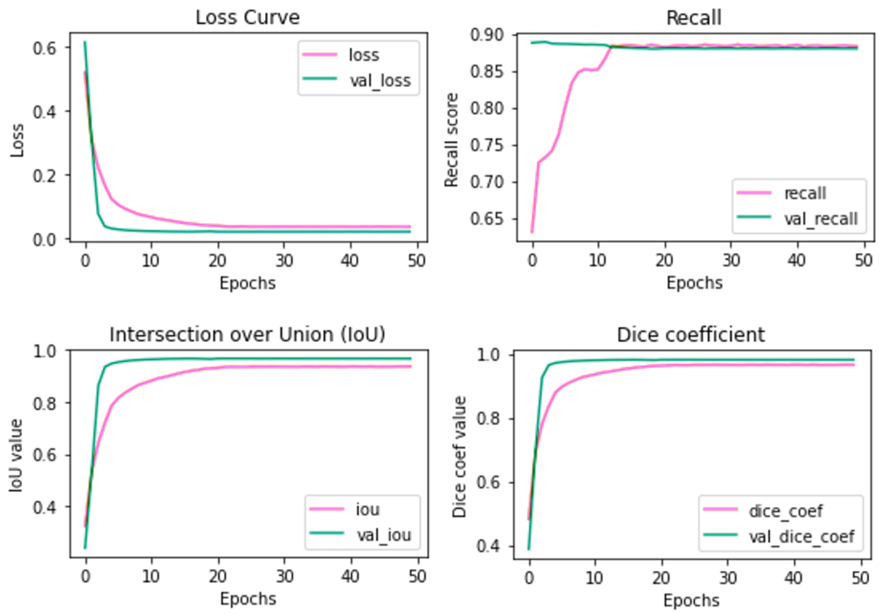

Fig. 5. Training Curve of horizontal voting, (a) Training for Segmented Image (b) Training Curve for Non-Segmented Image

ensemble model compare to the single models by 4.9%, 3.6%, 2.97%for segmented based approach and 5.73%, 3.5%, 3.2% gain for segmented free approaches. It is observed that the segmented based approach has a loss of 10.89% in accuracy even though there is a loss, the segmented approach can be justified when the dataset is large. We also considered 20 milliseconds(ms) less inference time and 50 megabytes(Mb) less memory usage.

Table 1. The perfomance of single and Deep ensemble model for both segmented and segmented free approach for COVID-19 detection.

Data Pattern	Framework	Precision	Recall	F1-score	Accuracy
Segmented	MobileNetV3	0.8652	0.8619	0.8623	0.8619
	ResNet152	0.8758	0.8742	0.8743	0.8742
	CNN	0.8782	0.8772	0.8770	0.8812
	Proposed method	0.9125	0.89159	0.8960	0.9109
Segmented-Free	MobileNetV3	0.9405	0.9437	0.9421	0.9473
	ResNet152	0.9019	0.9209	0.9110	0.9209
	CNN	0.9323	0.9341	0.9332	0.9393
	Proposed method	0.9485	0.9530	0.9507	0.9562

The confusion matrix of segmented image using deep ensemble framework is shown in this Figure 6.

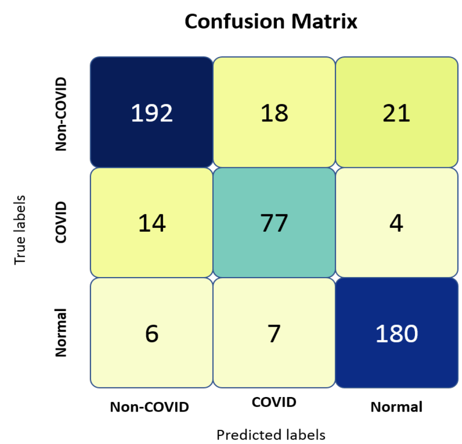

Fig. 6. Confusion matrix of segmented image

In Table 2 the comparative study with the Teixeira et al. is presented. It is observed that for both segmented and segmented free approaches our methods gives 1.5%, high in accuracy and 1.3% improved f1-score.

Table 2. Comparative study of F1-score of the proposed and state-of-the-art using RYDLS-20-v2 [21].

Data Pattern	Framework	COVID-19	Lung Opacity	Normal	Macro-Avg
Segmented	VGG16	0.8300	0.8800	0.9000	0.8700
	ResNet50V2	0.7800	0.8700	0.9100	0.8642
	InceptionV3	0.8300	0.8900	0.9200	0.8672
	Proposed method	**0.8919**	**0.9100**	**0.9310**	**0.9109**
Segmented-Free	MobileNetV3	0.9400	0.9100	0.9100	0.9200
	ResNet50V2	0.9100	0.9000	0.9200	0.9100
	InceptionV3	0.8600	0.9000	0.9100	0.9000
	Proposed method	**0.9520**	**0.9212**	**0.9315**	**0.9321**

5 Conclusion

The chest x-ray images are segmented to find out the ROI of lungs using U-Net based architecture is presented. A deep ensemble framework work is proposed to detect COVID-19 disease from the pool of chest X-ray images of normal, Pneumonia, and COVID-19 for both segment-free and segmented lung images. This framework is composed of two standard models and a developed CNN network. It has been observed that for segmented free approach, the accuracy of COVID-19 detection, than the segmented approach significantly improved. Though the performance of segmented-based approach is less, but this approach is very much essential for huge volume of data where memory consumption is an issue for the low resource platform. In the future, we will consider improving the performance of segmentation based approach by considering new deep learning models.

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