Using Image Segmentation to improve Covid-19 detection in Chest X-Rays

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Abstract

The COVID-19 pandemic, which began in December 2019, has resulted in numerous deaths and impacted every aspect of life. RT-PCR tests for Covid-19 Detection suffers from low accuracy, delay and low sensitivity. Therefore, deep learning is a useful tool due to the availability of various medical image sources such as CXR, CT, and MRI to fight against the COVID-19 detection. Here, we present a ***Custom U-Net*** *architecture - a modified U-Net architecture that incorporates residual units in each encoder and decoder block of the architecture. We also introduced new custom loss - an aggregation of binary cross-entropy loss, dice coefficient loss, and inverse dice coefficient loss. With careful selection of data augmentation techniques, our Custom U-Net achieved the accuracy of 91.89% and IOU of 88.36%. Using Custom U-Net, we segment regions of interest from CXR images and then employed a CNN-based classifier to perform COVID-19 detection on these segmented images, achieving an accuracy of 94.13%..*

1. Introduction

The COVID-19 pandemic, characterized by an exponential infection rate, has caused a strain on healthcare systems worldwide. COVID-19 is typically diagnosed using Reverse Transcription Polymerase Chain Reaction (RT-PCR), but this method has been shown to have low accuracy, a delay in results, and low sensitivity. Early diagnosis and treatment of a disease can improve the chances of success, and this is especially important in the case of a contagious disease like COVID-19. To aid in the diagnosis of COVID-19, wearable medical sensors and artificial neural networks can be used to analyze physiological and questionnaire data to classify patients. This can help to reduce the spread of the disease within the community [5].Radiography images, such as chest X-rays (CXR) or computed tomography (CT), are commonly used to diagnose lung-related conditions like pneumonia and tuberculosis, and can also be useful in detecting COVID-19. CXR has the advantage of being able to be easily performed with portable X-ray machines, allowing for faster and more accurate diagnosis of COVID-19. Additionally, CXR has the potential to detect COVID-19 with the aid of artificial intelligence and is less deleterious to the body compared to CT.

Hence, we present Custom U-Net - an Image Segmentation approach to improve the Covid-19 Detection in Chest X-Ray(CXR) images. Custom U-Net is modifed version of original U-Net [9]. Similar to U-Net [9], our architecture has a contracting path that captures context and a symmetric expanding path that allows for precise localization. In order to better understand the data flow from initial to last layers, we incorporated residual units in the U-Net architecture. We created a custom loss - an accumulation of binary cross-entropy loss, dice coefficient loss, and inverse dice coefficient loss. Dice-coefficient loss works well in case of class imbalance and our data-set has 72% more Normal images as compared to Covid images. We also employed gamma correction and carefully shortlisted data augmentation techniques to further improve our model.

2. Related Work

Researchers have been working to use AI-based techniques, including transfer learning, new network architectures, and ensemble methods, to detect COVID-19 using X-ray images. Some studies have

reported high accuracy rates in classifying COVID-19, normal, and other lung diseases, although the datasets used for training machine learning models have often been small. For example, Apostolopoulos et al. [2] reported an accuracy of 96.78% in detecting COVID-19 from bacterial pneumonia and normal X-rays in a dataset of 1427 X-rays, while Abbas et al. [1] reported an accuracy of 95.12% using a pre-trained CNN model with a small database of 196 X-ray images.
Minaee et al. [8] reported a specificity and sensitivity of 90% and 97%, respectively, using the ChexPert dataset. These promising results suggest that deep machine learning models can be effective in detecting COVID-19, even with small datasets. Khan et al. [6] explored the use of a limited number of machine learning algorithms for a four-class classification problem (COVID-19, bacterial pneumonia, viral pneumonia, and normal) with a very small dataset.

3. Our Approach

3.1. Architecture

We propose ***Custom U-Net*** - an Image Segmentation approach to improve the Covid-19 Detection in Chest X-Ray(CXR) images. Our architecture is similar to U-Net and has a contracting path that captures context and a symmetric expanding path that allows for precise localization. We added residual units to the U-Net architecture to better understand the flow of data from the initial to the final layers(Figure 2). We also created a custom loss that is a combination of binary cross-entropy loss, dice coefficient loss, and inverse dice coefficient loss. The dice coefficient loss is particularly useful in the case of class imbalance, which is present in our dataset, which has 72% more normal images compared to COVID-19 images. To further improve our model, we applied gamma correction and carefully selected data augmentation techniques. We took inspiration from ResUNet [3] that also uses the residual connections in the U-Net, but its architecture is quite complicated and memory-intensive. Additional to residual units, they have used atrous convolutions and pyramid scene parsing. Our approach gives good results while not being intricate at the same time. We obtained segmented images from our architecture and used those images as an input to the basic CNN classifier predicting whether the input is COVID-19 positive or not. Our complete architecture is shown in Figure 1.

3.2. Dataset

For the dataset, we used Covid-19 Radiograph Dataset (COVQU) [10]. It consists of 3,616 positive COVID-19 CXR images and 10,192 Normal CXR images. Each of theses images has corresponding segmented CXR masks to train the ***Custom U-Net***.
Due to class imbalance in the dataset, we have incorporated certain data augmentation techniques such as cropping, rotation and horizontal flip. We have also employed gamma correction - a technique that is used to adjust the luminance (brightness) of an image or video to compensate for the nonlinear response of a display device. We applied gamma correction into the input images before feeding into the model. This approach helps to improve the contrast and visual quality of the images which in turn can help our model to learn more effectively.

4. Experiments

4.1. Covid-19 detection without Data Augmentation and Image Segmentation

We use two architectures, i.e. a Custom CNN(Figure 5) and a ResNet [4], for the classification task. As shown in the Tab. 1, ResNet achieves the accuracy of 93.56% as compared to the custom CNN

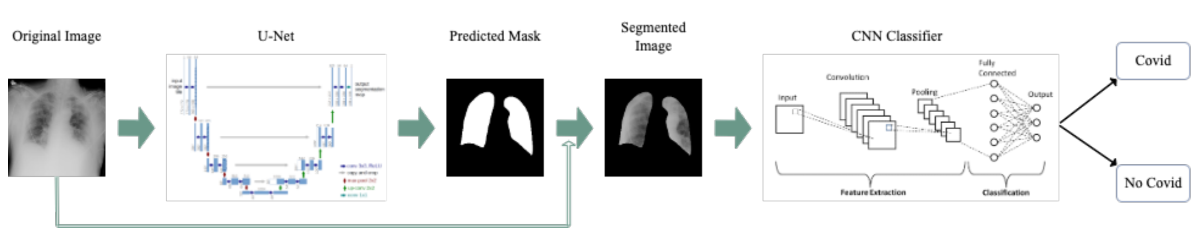


Figure 1. Segmenting CXR Image using U-Net. Then, using a CNN classifier to detect Covid-19 in segmented image.

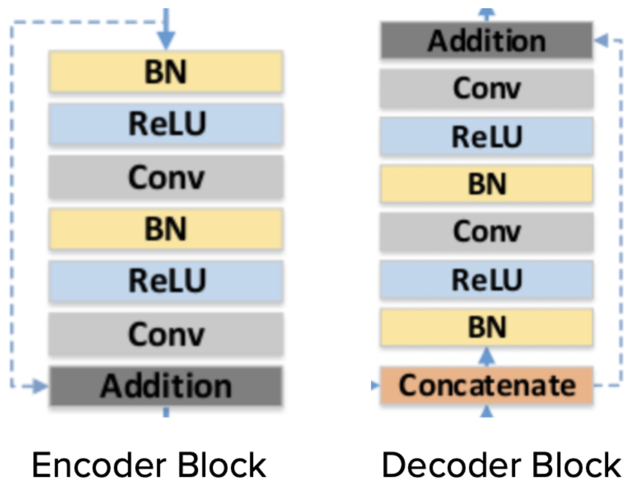


Figure 2. Custom U-Net Encoder & Decoder

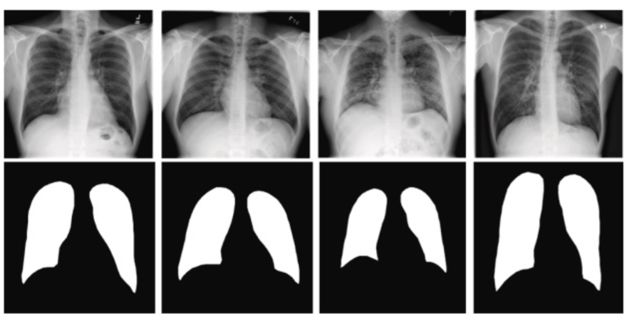


Figure 3. Covid-19 Radiograph Dataset

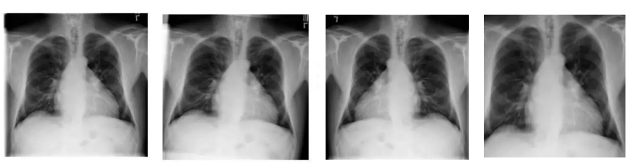
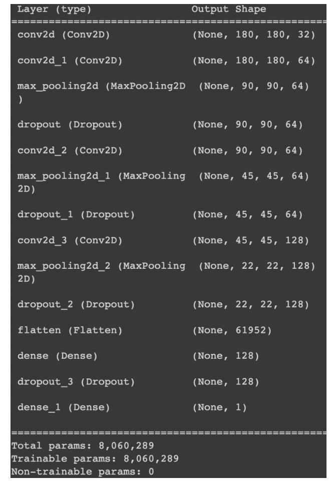


Figure 4. Data Augmentation with Rotation, Horizontal Flip and Crop

model with an accuracy of 90.54%. Also, we can observe in Figure 6 that the validation loss did not improve after 26 epochs for ResNet. For the basic custom CNN model, there is no loss improvement after 20 epochs.



```
Layer (type)                 Output Shape
=================================================================
conv2d (Conv2D)              (None, 180, 180, 32)

conv2d_1 (Conv2D)            (None, 180, 180, 64)

max_pooling2d (MaxPooling2D  (None, 90, 90, 64)
)

dropout (Dropout)            (None, 90, 90, 64)

conv2d_2 (Conv2D)            (None, 90, 90, 64)

max_pooling2d_1 (MaxPooling  (None, 45, 45, 64)
2D)

dropout_1 (Dropout)          (None, 45, 45, 64)

conv2d_3 (Conv2D)            (None, 45, 45, 128)

max_pooling2d_2 (MaxPooling  (None, 22, 22, 128)
2D)

dropout_2 (Dropout)          (None, 22, 22, 128)

flatten (Flatten)            (None, 61952)

dense (Dense)                (None, 128)

dropout_3 (Dropout)          (None, 128)

dense_1 (Dense)              (None, 1)

=================================================================
Total params: 8,060,289
Trainable params: 8,060,289
Non-trainable params: 0
```

Figure 5. Custom CNN-model

Model	**Accuracy**
Custom CNN	90.54%
ResNet	**93.56%**

Table 1. Covid-19 detection without Image Segmentation & Data augmentation

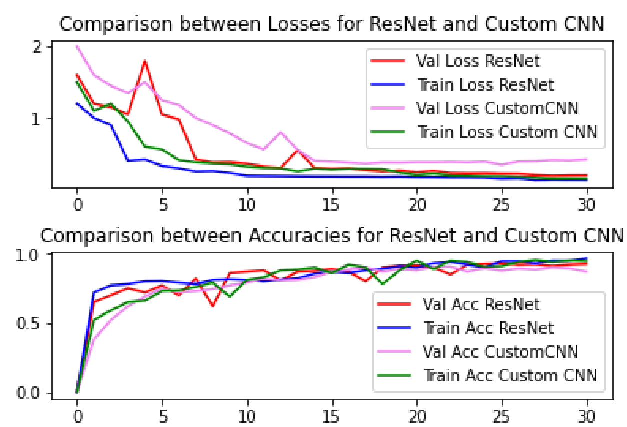


Figure 6. Comparison between ResNet & Custom CNN

4.2. Image segmentation using U-Net and Custom U-Net

Initially, we use the vanilla U-Net architecture to segment the CXR images into lung region vs non-lung region. We will use these segmented images for classification. Following that, we used Custom U-Net for image segmentation. We observe the results with and without using data augmentation and gamma correc-

Figure 7. Image Segmentation Results

tion. Predicted image segmentation mask sample can be seen in Figure 7.

We use accuracy (Total number of true pixels/All pixels) and IoU as our evaluation metrics. The results are shown in Tab. 2.

Model	Accuracy	IoU
U-Net	90.23%	86.52%
Custom U-Net	91.37%	88.21%
Custom U-Net + Data Augmentation	91.62%	**88.47**%
Custom U-Net + Data Augmentation + Gamma Correction	**91.89**%	88.36%

Table 2. Image Segmentation using U-Net

4.3. Covid-19 Detection with Image Segmentation

Here we combine the best model from basic Covid-19 detection(without image segmentation) and Custom U-Net. As seen from the Tab. 3, ResNet in combination our Custom U-Net gives **94.13%** accuracy, outperforming the basic ResNet classification model. The loss and accuracy curves are shown in Figure 8.

Model	Accuracy
ResNet	93.56%
CustomCNN	90.54%
ResNet + Image Segmentation	**94.13**%
CustomCNN+Image Segmentation	89.86%

Table 3. Classification with Image Segmentation

5. Conclusion

In conclusion, we completed following objectives -

- Created ***Custom U-Net*** with residual units and custom loss. Our model with data augmentation helped in improving the IoU for image segmentation.
- Implemented Gamma correction but it does not give significant improvement on the accuracy or IoU for image segmentation.
- Implemented Custom CNN. It was observed that ResNet performed better than our CustomCNN on COVID-19 detection.
- We uploaded the zip file containing our code and the sample test set.

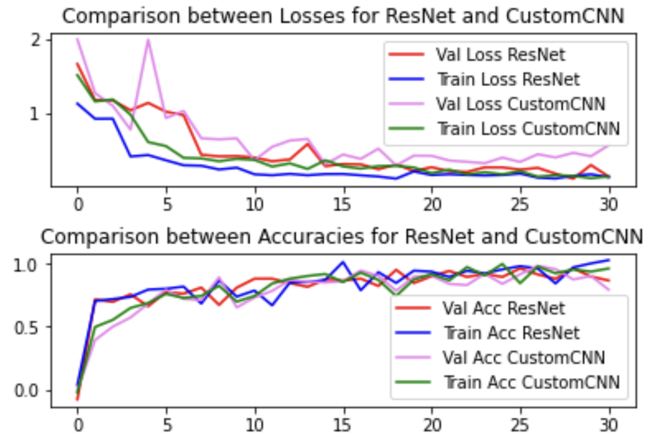


Figure 8. Comparison between ResNet & Custom CNN using Image Segmentation

6. Team Members Contribution

Agam:

- Implemented Custom CNN model for Covid-19 Classification.
- Used data augmentation techniques such as horizontal flip, crop and rotation.
- Performed quantitative analysis on the dataset.

Harsh:

- Implemented Custom U-Net - added residual units and custom loss function to improve the image segmentation on the Chest X-ray images.
- Employed gamma correction on input images.
- Performed qualitative analysis on the dataset.

7. Future Work

- Tweaking Custom CNN to improve accuracy using image segmentation
- Interpreting Trained model using Grad-CAM, SHAP [7]

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