Machine Learning in Medicine - Practical 3

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I. Introduction

This report presents the application of U-Net deep learning model for segmenting chest X-ray images into infection masks and lung masks using the COVID-QU-Ex dataset, which is collected from Kaggle.The aim is to demonstrate on demonstrating how U-Net can effectively extract important regions from medical X-ray images, which is an essential step in automated COVID-19 analysis.

II. Dataset

The COVID-QU-Ex dataset was developed by Qatar University and is publicity available on Kaggle. It contains a total of 33,920 chest X-ray (CXR) images, which are widely used for research in COVID-19 detection and lung infection analysis

The dataset is divided into three categories:

- 11,956 Images about COVID-19
- 11,263 Non-COVID infections Images
- 10,701 Normal Images

Fig. 1. Covid-19

Fig. 2. Non-Covid

Fig. 3. Normal

In addition to classification labels, the dataset also provides segmentation masks for lung regions and infections areas. These mark allow pixel-level analysis, making the dataset especially suitable for image segmentation tasks.

III. Problem Definition

The COVID-19 pandemic has had a severe impact on global health, resulting in a large number of infections and deaths worldwide. One of the major challenges in managing the disease is accurately identifying and analyzing infected regions in the lungs. Chest X-ray images play an important role in supporting medical diagnosis; however, manual analysis by medical experts is time-consuming and highly dependent on experience.

To better understand the spread and severity of lung infections, it is necessary to segment lung regions and infection areas from chest X-ray images. This information can help doctors assess disease progression, evaluate treatment effectiveness, and support further medical research, including vaccine and drug development.

Therefore, applying deep learning techniques, especially image segmentation models such as U-Net, becomes essential. These models can automatically detect and segment infected regions with high accuracy, reducing the workload of medical professionals and improving the efficiency and reliability of COVID-19 infection analysis.

IV. Methodology

For each chest X-ray image, we need to find the location of lung and area of infections. The Model for this task is U - Net. For constructing the structure of this model, Double Convolution is applied, which is build by two Single Convolutional Layers for each layer contains one convolutional 2D layer, batch normalization and ReLU activation function.

The structure of U - Net model:

- Encoder contains double convolutional layer followed by a maxpooling2D (kernel size = 2x2, stride =2).
- Bottleneck layer is located between encoder and decoder layers. It applied another double convolutional layer with higher input channel and output channel.
- Decoder uses transposed convolution layers to upsample the feature maps. After each upsampling step, the feature maps are concatenated with the corresponding encoder feature maps through skip connections.
- Skip connection help preserve important spatial details lost during downsampling and improve segmentation accuracy, especially around object boundaries.

V. Evaluation and Metric

Dice score and IOU score are applied to evaluate the the performance of U - Net Model. In the training processing, my model trained over 30 epochs and the figure for the last epoch with 0.2947 Loss, Dice score 0.6785, IoU 0.6473.

The final evaluation after training process:

- Dice Lung: 0.5767
- IoU Lung: 0.9344
- Dice Infection: 0.8692
- IoU Infection: 0.3421

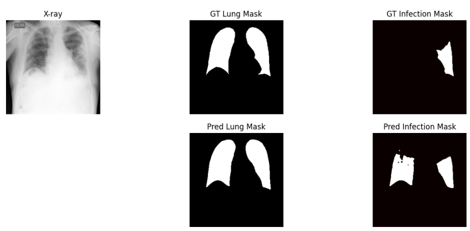

Fig. 4. Prediction Lung Mask and Infection Area

VI. Conclusion

In this study, a U-Net–based deep learning model was applied to segment lung regions and infection areas from chest X-ray images in the COVID-QU-Ex dataset. The experimental results show that the model performs well in lung segmentation, but its performance on infection segmentation remains limited.

From the qualitative results shown in the figure, the predicted lung masks closely match the ground truth masks, indicating that the model is able to accurately capture the overall shape and location of the lungs. This observation is supported by the evaluation metrics, where the lung segmentation achieves a high IoU score of 0.9344, demonstrating strong spatial overlap between the predicted and ground truth lung regions. However, the Dice score for lung segmentation is relatively lower (0.5737), which may be influenced by class imbalance or boundary inaccuracies.

In contrast, infection segmentation presents a greater challenge. Although the Dice score for infection segmentation is relatively high (0.8692), the IoU score is significantly lower (0.3421). This inconsistency indicates that while the model can detect infection regions, it struggles to accurately localize their exact boundaries. Visually, the predicted infection masks contain false positive regions and do not fully align with the ground truth masks. This behavior is expected because infection areas in chest X-ray images are often small, irregular, and have low contrast compared to lung regions.

Overall, the results demonstrate that the U-Net model is effective for lung segmentation but less reliable for precise infection segmentation. This highlights the need for further optimization when dealing with small and complex target regions such as COVID-19 infections.

VII. Limitations and Future Improvements

Despite achieving promising results in lung segmentation, the proposed U-Net model shows limitations in accurately segmenting infection regions. Infection areas in chest X-ray images are often small, irregular, and have low contrast, which makes precise boundary detection difficult. In addition, class imbalance between background, lung, and infection pixels negatively affects the reliability of the evaluation metrics, leading to unstable Dice and IoU scores. To improve performance, future work should focus on using more suitable loss functions such as a combination of Dice loss and Binary Cross-Entropy or Focal loss to better handle small target regions. Stronger data augmentation and higher-resolution inputs may help the model learn finer details of infection patterns. Moreover, advanced architectures such as Attention U-Net or UNet++ could improve feature representation by allowing the model to focus more on relevant regions. Training a separate infection segmentation model restricted to the lung area and applying post-processing techniques to remove noise are also potential directions to enhance segmentation accuracy.