4th Bioinformatics and Biodiversity Conference
Volume 2023
http://dx.doi.org/10.11594/nstp.2023.3721

NST Proceedings
OPEN ACCESS

Conference Paper

Leprosy Early Detection Through Binary Segmentation Using ResU-Net

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ABSTRACT

Leprosy is a chronic infectious disease caused by Mycobacterium leprae that can lead to physical deformity if left untreated. Indonesia currently ranks third in the world for leprosy prevalence, with the highest concentration of cases found in the provinces of West Papua, North Maluku, and Papua. These provinces, located in the eastern region of Indonesia, face numerous challenges in terms of healthcare accessibility for early leprosy detection due to various factors and novel, more accessible method to detect leprosy is urgently needed. In this study, we introduce an innovative approach to early leprosy detection by leveraging the ResU-Net model. The ResU-Net, a hybrid architecture, combines the robust U-Net framework, renowned for its efficacy in medical image segmentation, with the powerful ResNet-50 and ResNet-101 backbones. The incorporation of ResNet-50 and ResNet-101 enhances the model's capability to extract intricate features from the target image, allowing for a more comprehensive analysis and ultimately, a more accurate and early detection of leprosy. To train and validate our model, we employ the CO2Wounds Leprosy dataset, a comprehensive collection of medical images showcasing images of leprosy taken using smartphone. The research results demonstrate the promising potential of ResU-Net in accurately identifying leprosy-affected areas within these images with highest IoU scores of around 80% with the ResNet101 backbone and around 79% with the ResNet50 backbone. This method holds great potential for improving the management of leprosy in regions with high prevalence by enabling accessible and timely interventions.

Keywords: Leprosy, binary segmentation, deep learning, UNet, ResNet, ResU-Net

Introduction

Leprosy is a chronic infectious diseases caused by Mycobacterium leprae and Mycobacterium lepromatosis which affects the skin and peripheral nerves. The disease can lead into physical deformities if left untreated. This effect makes the ancient people think that people with this disease is cursed and the patients are ostracized from society (Santacroce et al., 2018). Early signs of leprosy can be identified as a hypopigmented patch with reduced sense in the lesion, making the patient unable to differentiate hot and cold sensation. After that, the disease will continue to develop, enlarging the peripheral nerve at the skin lesion location and creating physical deformities to the carrier. In ancient times, leprosy patients were secluded from communities to prevent spreading. However, after the rise of antimicrobial therapy, leprosy can be cured with antimicrobial (Makhakhe, 2021).

The World Health Organization (WHO) has declared the disease to be eliminated as a global public health problem in 2000, the disease remains a major healthcare distress in many developing countries like India, Brazil, and Indonesia (Maymone et al., 2020). Indonesia is currently having the third largest leprosy patient in the world with the highest concentration of cases found in the provinces of West Papua and North Maluku (Prakoeswa et al., 2022). These provinces are located in the Eastern side of Indonesia that face numerous challenges in terms of healthcare accessibility for early leprosy detection. Novel and more accessible method to treat leprosy is urgently needed to solve this problem.

How to cite:
Simangunsong, A. J. B. (2023). Leprosy early detection through binary segmentation using ResU-Net. *4th Bioinformatics and Biodiversity Conference*. NST Proceedings. pages 166-174. doi: 10.11594/ nstp.2023.3721

One of the potential methods for early detection of leprosy is deep learning. If leprosy is detected during the early phase, patients can be treated immediately with antibiotics, preventing the development of the disease (Maymone et al., 2020). Utilizing deep learning in computer vision can lead to a more accessible treatment for leprosy. Deep learning has been widely used in medical imaging to detect certain disorders, such as lung cancer detection from early scans or melanoma detection by binary segmentation.

In this paper, the author suggests an innovative approach to early leprosy detection by leveraging the ResU-Net model. ResU-Net is a modified version of U-Net that incorporates residual blocks in its architecture. The author also incorporates ResNet as the backbone to extract more features. In this research, two models are the ResU-Net model created with ResNet-50 and ResNet-101 as the backbone. Then, the model will be evaluated from the mean IoU score of the model.

Material and Methods

Materials

The dataset used in this research is CO2Wounds. The dataset is created by Monroy *et al* in 2022 and contains 164 images and masks of leprosy skin lesion at various stages that's taken with a smartphone. The sample of the dataset can be observed in Figure 1 (Monroy et al., 2022).

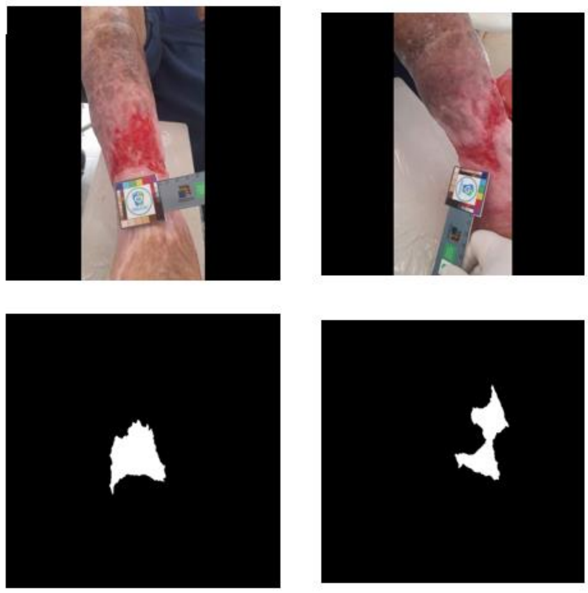

Figure 1. Sample of CO2Wounds Dataset (Monroy et al., 2022)

Data preprocessing

Image augmentation is performed to enrich the dataset by generating new images by resizing, random crop, random flip, rotate, and random brightness. Then, the data is used to train and evaluate the model.

ResU-Net

ResU-Net is a deep learning architecture to perform semantic segmentation in image dataset. It was first developed by Xin et al. (2017) to perform road extraction from aerial data; however, the architecture has been proven to be very useful in other cases like medical imaging (Salpea et al., 2023). The architecture is a combined version of U-Net and ResNet. It enhances the U-Net architecture by replacing the UNet building blocks with residual connections, enabling it to extract more features and perform better with less parameters (Xin et al., 2017).

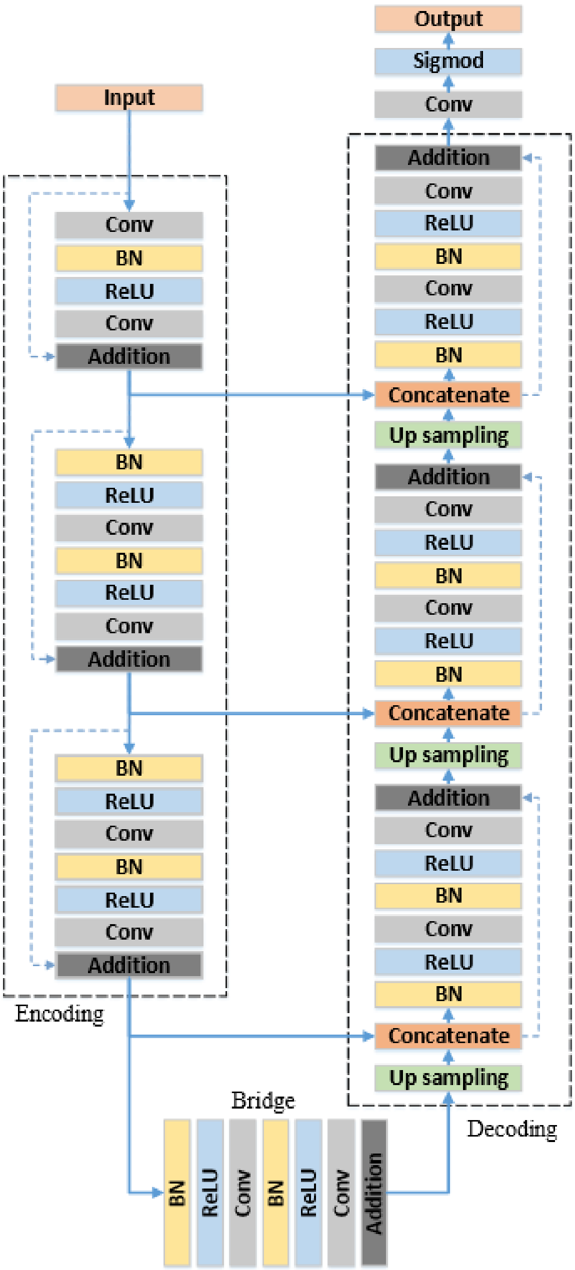

Figure 2. Proposed ResUNet Architecture by Xin et al. (2017)

U-Net is the base form of ResU-Net. U-Net is a deep convolutional neural network architecture designed for image segmentation tasks, particularly in the field of medical image analysis. It was introduced in the paper titled "U-Net: Convolutional Networks for Biomedical Image Segmentation" by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015. The central idea behind U-Net is to enable precise segmentation of objects or regions in an image. It achieves this through a unique architecture that combines the localization capabilities of a contracting path (downsampling) with the contextual information of an expansive path (upsampling) (Ronneberger et al., 2015).

U-Net is known for its effective performance in segmenting small, detailed structures within images, making it especially valuable in medical image segmentation tasks. It is crucial to leverage low level details while keeping high level semantic information to get good results in semantic segmentation. However, training a deep neural network for that purpose is extremely challenging because sufficient sample data may not be available. Using massive data augmentation, as is done in U-Net, is a further method. U-Net helps to alleviate the training challenge in addition to augmenting data. The idea here is that by copying low-level features to their corresponding high-level counterparts, a path for information propagation is created, making it easier for signals to propagate between low and high levels. This facilitates backward propagation during training and compensates for low-level finer details to high-level semantic features (Ronneberger et al., 2015).

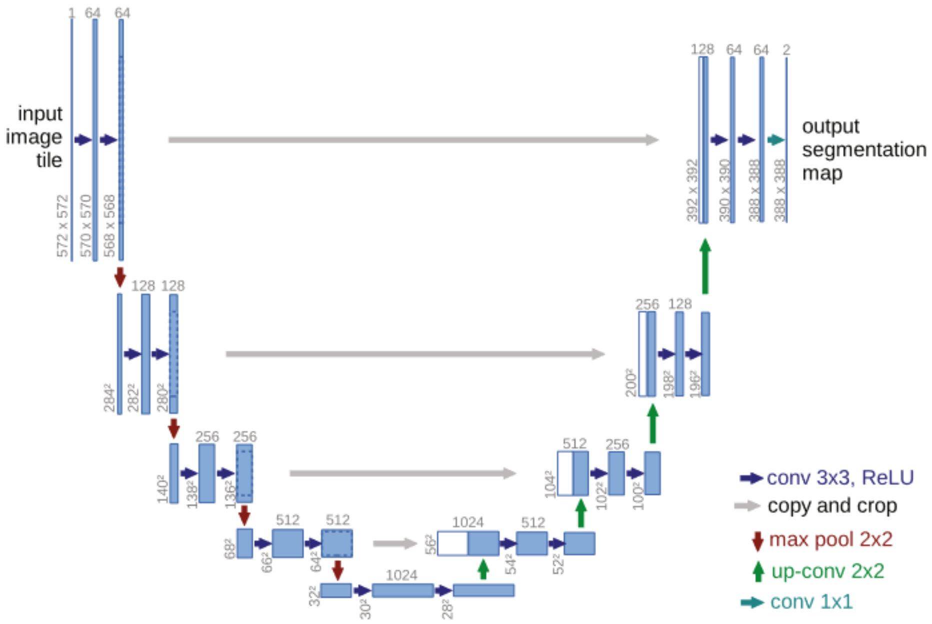

Figure. 3. Proposed UNet Architecture by Ronneberger et al. (2015)

To create a ResU-Net, Residual Networks (ResNet) is introduced to U-Net model. Residual Networks are a class of neural networks architecture which use residual blocks that contain skip connections. These skip connections allow information to bypass one or more layers in the network and the network can focuses on learning the changes required to transform the input which came from the skip connection into a desired output rather than learning the entire mapping from scratch (He et al., 2016).

A residual block in a ResNet is defined by the following equation:

$$F(x) = H(x) + x \tag{1}$$

In this equation, x represents the input to the residual block. H(x) is the residual mapping, the difference between the desired output and the input. F(x) is the output of the residual block, which is the sum of H(x) and x. By learning residual mapping, the network focus on learning the changes required to transform the input x into the desired output, rather than learning the entire mapping from scratch. If H(x) is close to zero, it means that the network has learned the identity mapping which help in the optimization process.

This approach addresses the vanishing gradient problem that occurs in very deep networks when gradients become too small during backpropagation. The skip connections enable the gradients to flow more easily through the network, allowing for the training of much deeper neural networks without encountering diminishing gradients. ResNets have had a profound impact on the field of deep learning, particularly in the domain of computer vision, due to their ability to effectively train extremely deep neural networks (He et al., 2016). By combining U-Net and ResNet into ResU-Net, more features can be extracted from the limited number of images.

Optimization

The model is optimized using Stochastic Gradient Descent (SGD) with momentum. SGD is a widely used algorithm in neural network optimization. The algorithm updates weights and bias parameters by adjusting them based on the negative gradient multiplied by a learning parameter (η) with the objective of minimizing the loss function (Bottou et al., 2012). The mathematical equation of SGD can be observed:

$$w_{ij} = w_{ij} + \Delta w_{ij} \quad (2)$$

Where:

$$w_{ij} = \eta \, \delta D/(\delta w_{ij}) \quad (3)$$

Stochastic Gradient with momentum is a variant of SGD that accelerates convergence, allowing it to potentially get stuck in low local minimums. This method s faster compared to the standard SGD due to the introduction of a momentum term. The mathematical equation of Stochastic Gradient with momentum can be observed:

$$\Delta w_{ij}(t+1) = -\frac{\eta \delta E}{\delta w_{ij}} + \alpha \Delta w_{ij}(t) \quad (4)$$

Performance evaluation

The metrics applied to evaluate the result are Mean Intersection Over Union (Mean IoU Score) and Jaccard loss score. Intersection Over Union is a common parameter r used to evaluate category segmentation model performance. It measures the similarity of the target region with the region labeled by the model. This measurement is used instead of accuracy because if the model selects all of the targeted areas but selects other areas other than the target, the accuracy will still be good. However, IoU score can penalize it (Rahman & Wang, 2016). IoU is defined by the following equation where TP, FP, and FN is the true positive, false positive, and false negative counts.

$$IoU = \frac{TP}{FP + TP + FN} \quad (5)$$

However, in this research, mean IoU is used because there are several divided regions to be detected by the model. Mean IoU will measure the model capability to detect every part of the divided region. To evaluate the metrics that is used for segmentation, Jacard loss score is used. The model will optimize itself by observing the resulting IoU score (Bertels et al., 2019). Jacard loss score is defined by the equation:

$$L_{IoU} = 1 - \frac{\sum_{c=1}^{C} \sum_{i=1}^{N} g_i^c s_i^c}{\sum_{c=1}^{C} \sum_{i=1}^{N} (g_i^c + s_i^c - g_i^c s_i^c)}. \quad (6)$$

Results and Discussion

In this research, the entire code is run on free Google Collab platform. A generator dataset is created from the available dataset to generate modified images by implementing various treatments just as explained in the data preprocessing. After that, model architecture was created.

The model used can optimize automatically with Stochastic Gradient Descent with a momentum parameter of 0.9 and the learning rate is optimized by TensorFlow ExponentialDecay class with the decay step set to 10 and the decay rate is set to 0.96. The batch size used for this model is 4 because of the limitations of Google Collab's computational capacity. The model is then trained in 90 epochs. The results yielded by the model can be seen in the Figures.

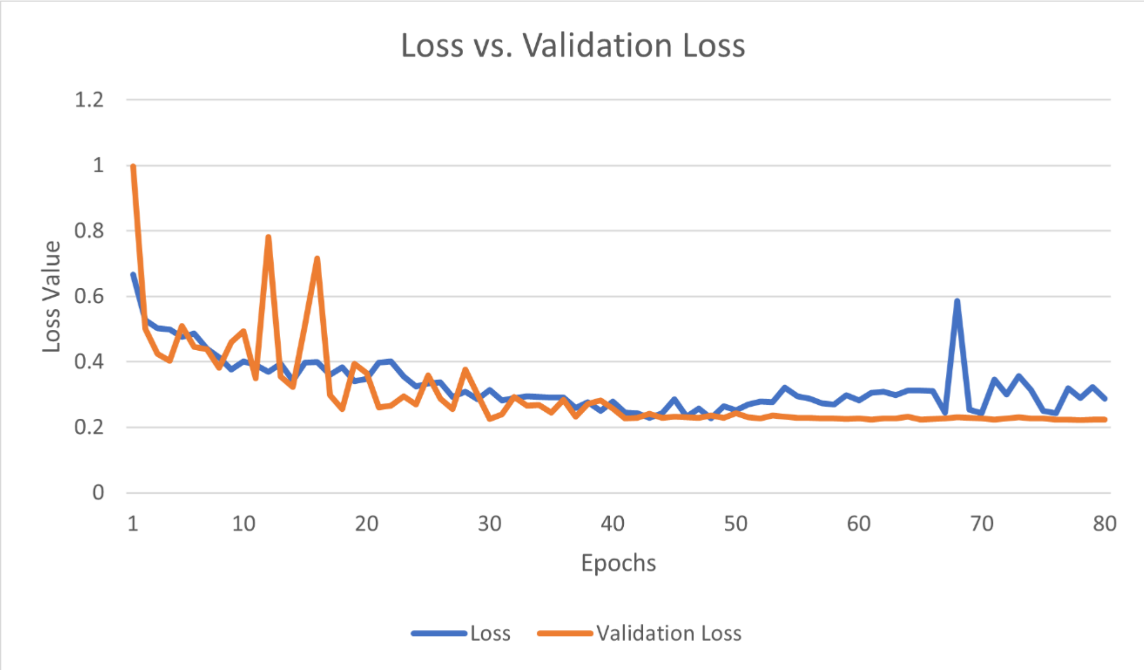

Figure 5. Loss curve of the ResU-Net model with ResNet-50 backbone

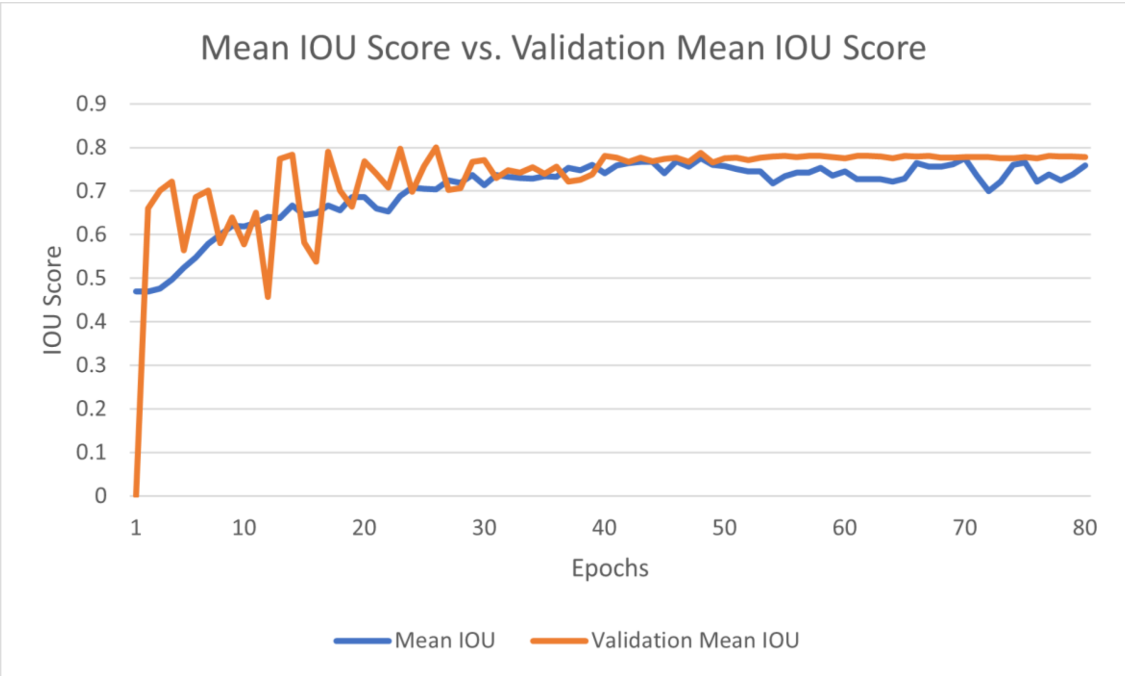

Figure 6. Mean IoU curve of the ResU-Net model with ResNet-50 backbone

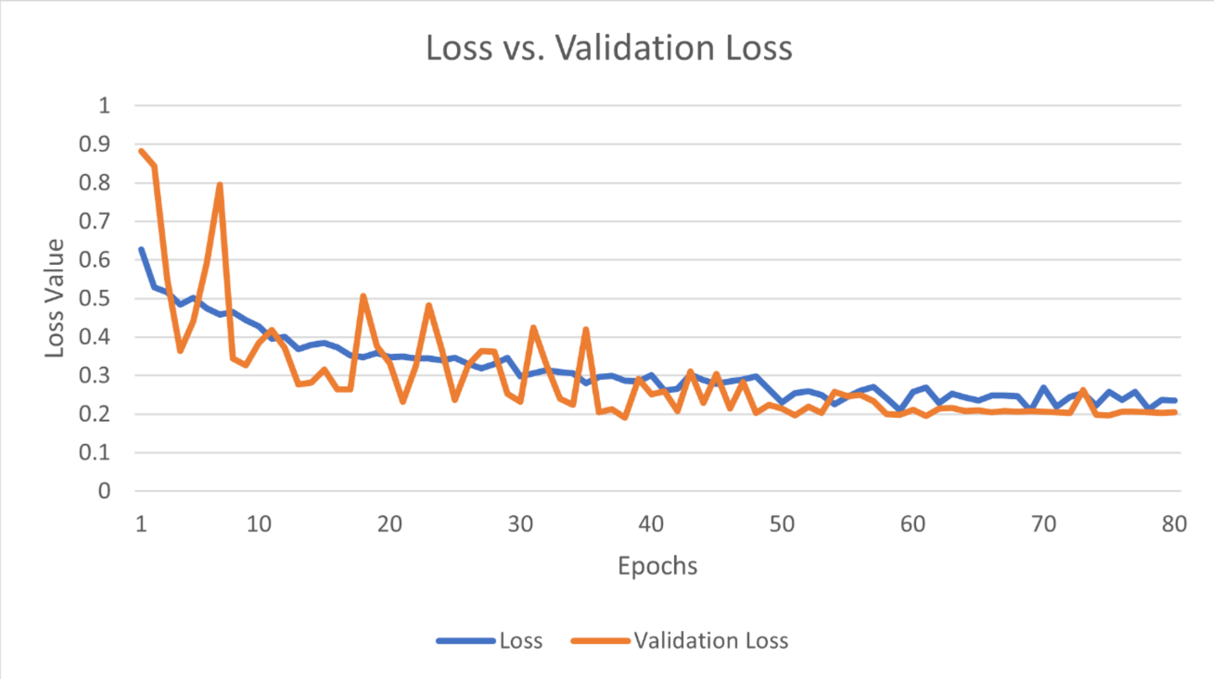

Figure 7. Loss curve of the ResU-Net model with ResNet-101 backbone

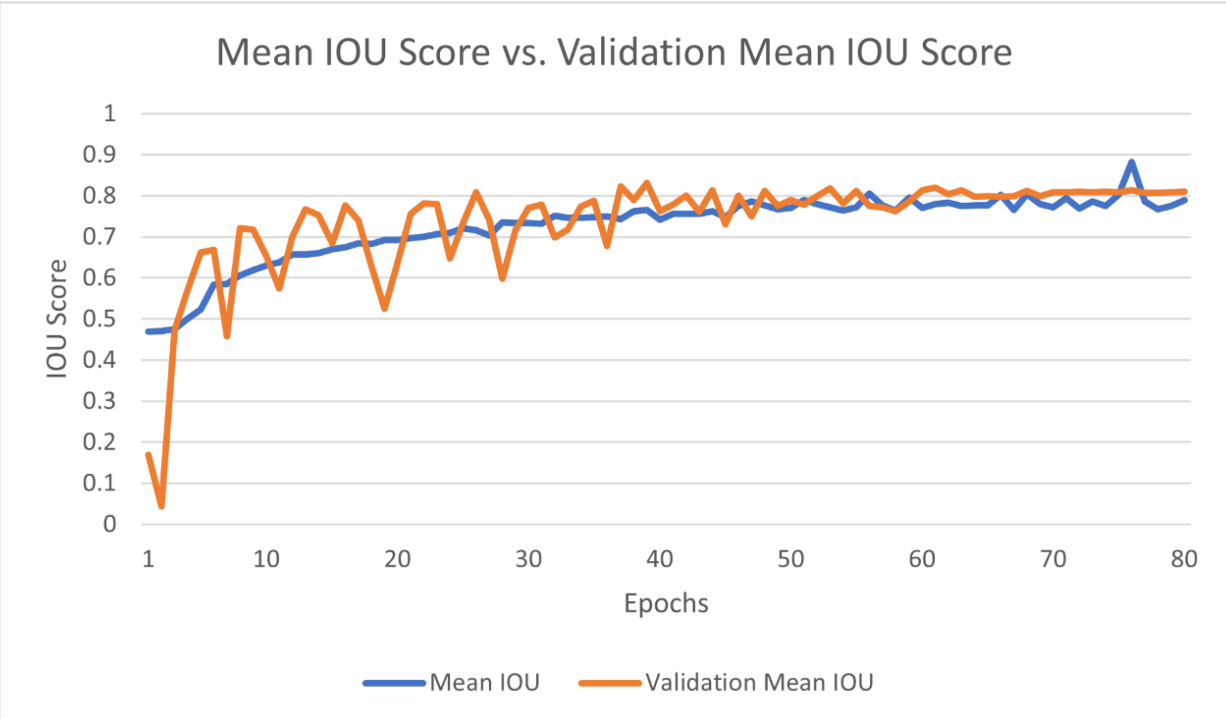

Figure 8. Mean IoU curve of the ResU-Net model with ResNet-101 backbone

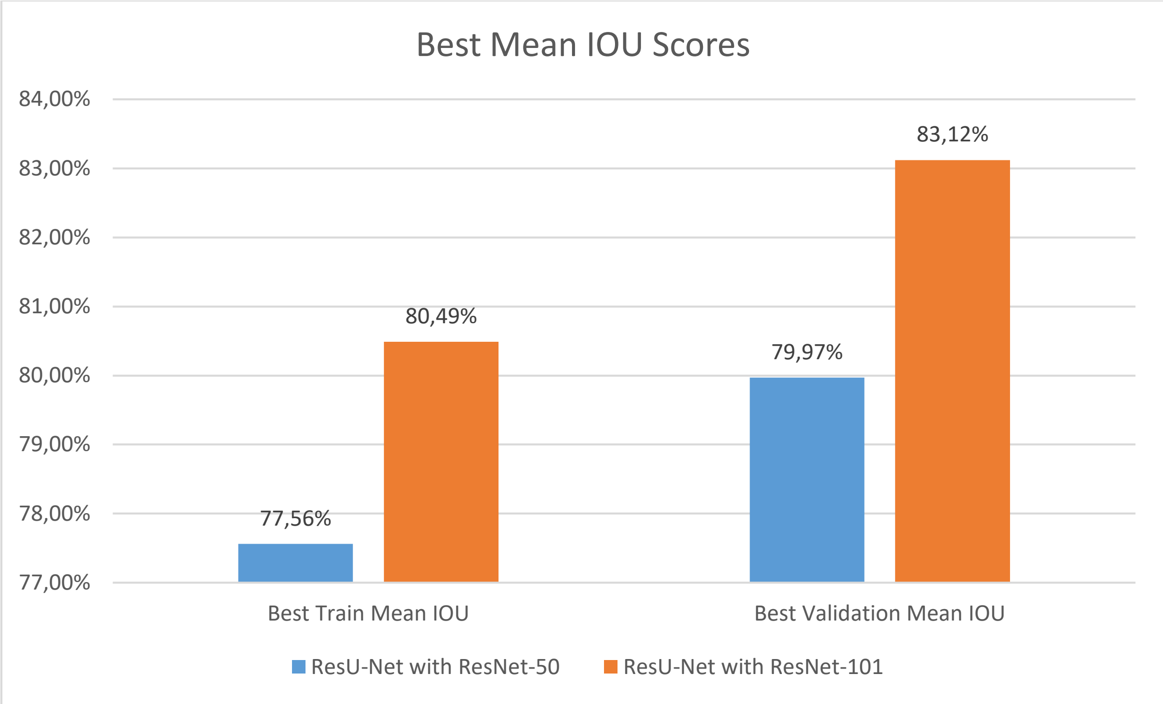

Figure 9. Mean IoU curve of the ResU-Net model with ResNet-101 backbone

The analysis shows that both models managed to learn well from the provided dataset and ResU-Net with ResNet-101 backbone performed slightly better than ResU-Net with ResNet-50 backbone. ResNet-101 has more layers compared to ResNet-50, enabling it to extract more features and impacting the performance of the model.

Conclusion

The resU-Net model showed promising results in the detection of Leprosy from the dataset. Two ResU-Net models with different backbones, ResNet-50 and ResNet-101, were created with the leprosy image dataset. ResU-Net with ResNet-101 backbone showed a higher mean IoU score compared to ResU-Net with ResNet-50 backbone. According to the results, the best model possesses the best mean IoU score of 80.49% and the best validation mean IoU score of 83.12%. The best segmentation model has the potential to be developed further to detect leprosy.

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