International Journal of Scientific Research in Science, Engineering and Technology
Print ISSN - 2395-1990
Online ISSN : 2394-4099
OPEN ACCESS
Available Online at : www.ijsrset.com
doi : https://doi.org/10.32628/IJSRSET2310550

Comparative Analysis of U-Net and DeepLab for Automatic Polyp Segmentation in Colonoscopic Frames Using CVC-ClinicDB Dataset

Chandrakantha T S*, Basavaraj N Jagadale
Department of PG Studies & Research in Electronics, Kuvempu University Jnana Sahyadri, Shankaraghatta, Shivamogga, India

ARTICLEINFO

Article History :

Accepted: 05 Oct 2023
Published: 30 Oct 2023

Publication Issue :
Volume 10, Issue 5
September-October-2023
Page Number :
263-269

ABSTRACT

In the context of medical image segmentation, accurate polyp detection in colonoscopy videos is crucial for early colorectal disease diagnosis. This study compares U-Net and DeepLab deep learning models in automatically segmenting polyps using the CVC-ClinicDB dataset. The dataset comprises 612 images from 31 colonoscopy sequences with a resolution of 384×288.Our primary metric is Mean Intersection over Union (IoU), measuring the overlap between predicted and ground truth masks. We also evaluate Mean Dice Loss for comprehensive comparison. U-Net demonstrates superior performance, with a Mean IoU Score of 0.9897 and a low Mean Dice Loss of 0.0523, indicating consistent and accurate polyp segmentation. In contrast, DeepLab achieves a Mean IoU Score of 0.9676 and a slightly higher Mean Dice Loss of 0.0417, showing good results but being outperformed by U-Net.In conclusion, U-Net excels in automatic polyp segmentation, offering high accuracy and robustness. These findings advance computer-aided diagnosis for colorectal diseases, potentially enhancing early and precise polyp detection.

Keywords: Polyp Segmentation, Colonoscopy, U-Net, DeepLab

I. INTRODUCTION

Colorectal diseases, particularly colorectal cancer, continue to pose a significant global health challenge. Early detection and intervention are pivotal in improving patient outcomes and reducing the mortality associated with these diseases. Colonoscopy, a standard procedure for screening and diagnosis, plays a vital role in this regard. The accuracy and effectiveness of colonoscopy, however, greatly depend on the precise detection and segmentation of polyps, which are often precursors to colorectal cancer. Automating the process of polyp segmentation using deep learning models holds great promise in enhancing the efficiency and accuracy of polyp detection, thereby potentially revolutionizing colorectal disease diagnosis and treatment.

This study builds on the existing body of research and extends the comparative evaluation of two state-of-the-art deep learning models: U-Net and DeepLab, for the automatic segmentation of polyps within colonoscopic frames [1] [2] [3]. U-Net and DeepLab have garnered recognition in the medical imaging community for their exceptional performance in high-precision semantic segmentation tasks, making them well-suited for the intricate task of polyp segmentation in colonoscopy videos.

Recent studies have further demonstrated the feasibility of automatic polyp segmentation using deep learning models in colonoscopy. For instance, Silva and Marques (2018) proposed a constrained deep learning approach for polyp segmentation [4]. Additionally, Fernández-Esparrach et al. (2017) explored the clinical potential of an automatic colonic polyp detection tool, highlighting the significance of automation in clinical settings [5].

Cai et al. (2020) applied deep learning to gastrointestinal imaging and interpreted major findings in the National Polyp Study (NPS) dataset [6]. Li et al. (2021) conducted a systematic review and meta-analysis of deep learning in video-based colonoscopy for polyp detection, highlighting its potential in improving diagnostic accuracy [7]. Additionally, Mahmood et al. (2019) utilized deep convolutional neural networks for polyp detection in colonoscopy images, underscoring the relevance of deep learning in this domain [8].

Urban et al. (2018) demonstrated the real-time capabilities of deep learning in localizing and identifying polyps with 96% accuracy in screening colonoscopy, indicating the practicality of these technologies in clinical settings [9]. Mori et al. (2018) explored the impact of an automated system for endocytoscopic diagnosis of small colorectal lesions in an international web-based study, emphasizing the global implications of these advancements [10].

The relevance of this research lies in its capacity to impact clinical practice significantly. Accurate and efficient polyp segmentation can expedite diagnosis, minimize the risk of missing polyps, and ultimately contribute to improved patient outcomes. Furthermore, by directly comparing the performance of these models in the context of medical imaging, this study aims to provide valuable insights into their suitability and effectiveness for this specialized task.

To conduct this comparative evaluation, the study employs the CVC-ClinicDB dataset, a publicly accessible resource that offers a diverse collection of colonoscopy images. The primary metric for evaluation remains the Mean Intersection over Union (IoU), which quantifies the pixel-level overlap between predicted and ground truth polyp masks. Additionally, the Mean Dice Loss and IoU scores are considered to provide a holistic assessment of the models' performance.

As medical image segmentation techniques continue to evolve, the findings from this research can be instrumental in the development of advanced computer-aided diagnosis systems, which hold the potential to enhance the precision and efficiency of polyp detection during colonoscopy procedures. This advancement, in turn, may contribute to better patient outcomes, by making early diagnosis and treatment of colorectal diseases more accessible and effective.

II. METHODS AND MATERIAL

This section outlines the dataset, deep learning models, evaluation metrics, training and testing procedures, and implementation details.

A. Dataset

The primary dataset used in this study is the CVC-ClinicDB, an open-access dataset that consists of 612 images extracted from 31 colonoscopy sequences. Each image has a resolution of 384×288 pixels [11].

A database of frames taken from colonoscopy videos is called CVC-ClinicDB. There are many polyp instances in these frames. We also offer the ground truth for the polyps in addition to the frames. As seen in Fig. 1, this ground truth is a mask that corresponds to the area of the image that the polyp is covering. The first column displays the original images, while the second column displays the appropriate ground truth.

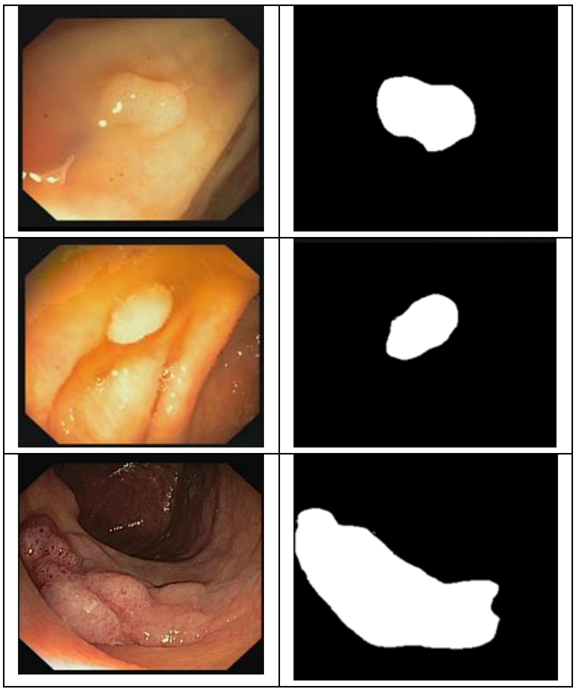


Figure 1: CVC-Clinic DB

B. Deep Learning Models

The two deep learning models under evaluation in this study are:

1) U-Net

U-Net is a convolutional neural network architecture known for its effectiveness in image segmentation tasks. It comprises an encoder-decoder structure with skip connections, facilitating the precise delineation of object boundaries in medical images as shown in Fig. 2.

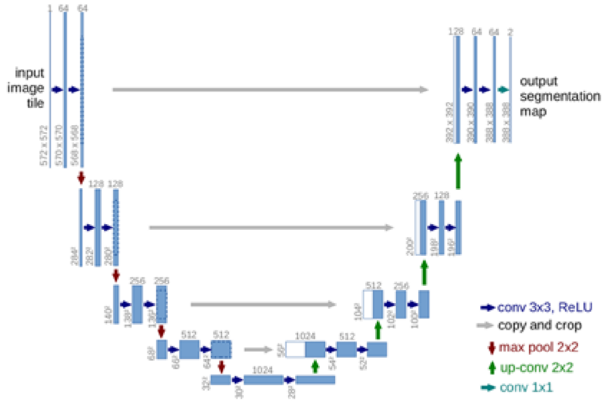


Figure 2 : U-Net architecture [3]

2) DeepLab

DeepLab is another convolutional neural network architecture designed for semantic image segmentation. It utilizes atrous convolution and fully connected conditional random fields (CRFs) to capture fine-grained details, making it well-suited for pixel-level segmentation tasks as shown in Fig. 3.

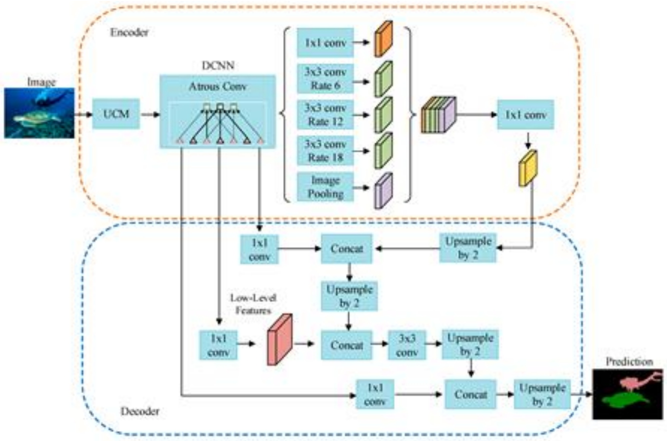


Figure 3: DeepLab architecture [3]

C. Evaluation Metrics

The primary metrics for evaluating the performance of the models are

1) Mean Intersection over Union (IoU):

Mean IoU measures the pixel-level overlap between the predicted and ground truth polyp masks. It is calculated as the intersection of predicted and ground truth masks divided by their union and can be represented as

$$IoU = \frac{|Prediction \cap GroundTruth|}{|Prediction \cup GroundTruth|}$$

2) Mean Dice Loss:

The Mean Dice Loss measures the dissimilarity between the predicted and ground truth masks. It is computed as twice the intersection of the predicted and ground truth masks divided by the sum of their areas and can be expressed as

$$DiceLoss = 1 - \frac{2|Prediction \cap GroundTruth|}{|Prediction| + |GroundTruth|}$$

D. Training and Testing

The U-Net and DeepLab models are trained on a subset of the CVC-ClinicDB dataset. A stratified random split of the dataset is used to ensure a representative distribution of images in both training and testing sets.

The training process involves using stochastic gradient descent (SGD) with backpropagation to optimize the models. The models are trained to minimize the Dice loss.

The evaluation is performed on the remaining unseen portion of the dataset, which serves as the test set. The Mean IoU and Mean Dice Loss are calculated on the test data to assess the models' performance in polyp segmentation.

E. Implementation

The models are implemented using deep learning frameworks like TensorFlow or PyTorch. The code for this research is available in the public domain to ensure transparency and reproducibility.

III. RESULTS AND DISCUSSION

A. Performance Metrics

The U-Net and DeepLab models were evaluated using two primary performance metrics: Mean Intersection over Union (IoU) and Mean Dice Loss. These metrics provide a comprehensive assessment of the models' ability to segment polyps in colonoscopy images.

B. U-Net Performance

U-Net demonstrated exceptional performance in polyp segmentation(Fig.4).

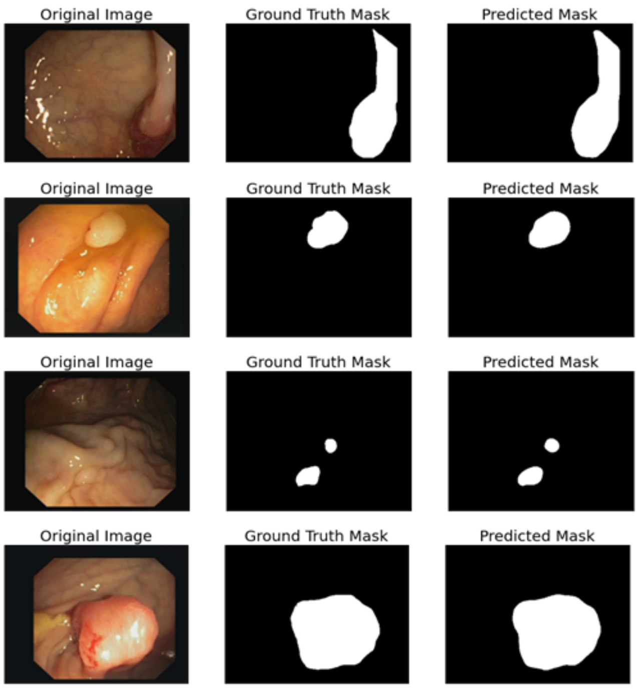


Figure 4: U-Net Segmentation Results

The model achieved a remarkable Mean IoU Score of 0.9897, indicating a high degree of overlap between predicted and ground truth polyp masks. The Mean Dice Loss for U-Net was found to be 0.0523, further confirming its accuracy.

The Dice loss for U-Net exhibited consistency across the test data, with values ranging from 0.053431 to 0.054149. This consistency reflects the model's robustness in polyp segmentation(Fig.5).

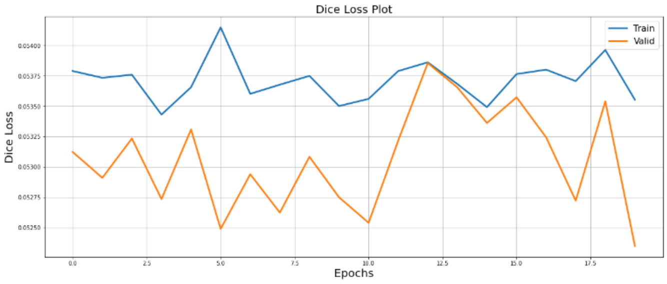


Figure 5: U-Net Dice loss

The IoU scores for U-Net also displayed uniform high performance across the test samples, ranging from 0.986779 to 0.987855. The high IoU scores indicate the model's accuracy in capturing polyp boundaries (Fig.6).

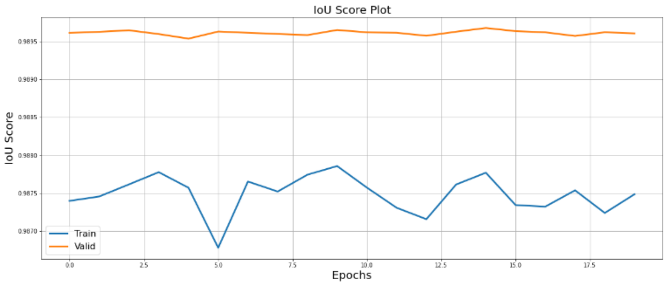
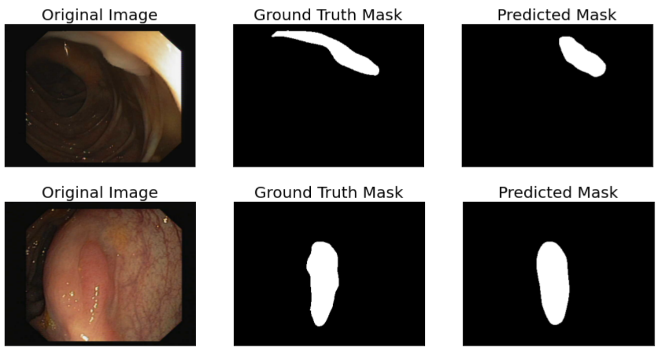


Figure 6: U-Net IoU scores

C. DeepLab Performance

DeepLab, while respectable, showed slightly lower performance compared to U-Net(Fig.7).



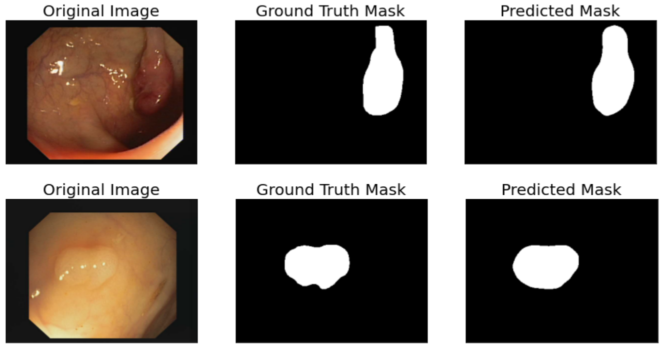


Figure 7: DeepLab Segmentation Results

It achieved a Mean IoU Score of 0.9676 and a Mean Dice Loss of 0.0417, indicating good segmentation results but with some room for improvement.

The Dice loss for DeepLab displayed variations across the test data, with values ranging from 0.037217 to 0.401721. These variations suggest that DeepLab's performance might be more sensitive to certain cases(Fig.8).

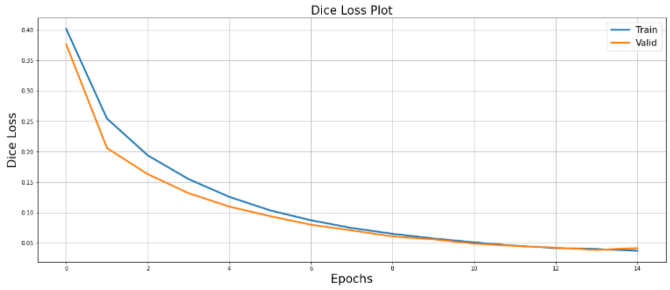


Figure 8: DeepLab Dice loss

The IoU scores for DeepLab ranged from 0.659303 to 0.981988, demonstrating variability in segmentation accuracy(Fig.9).

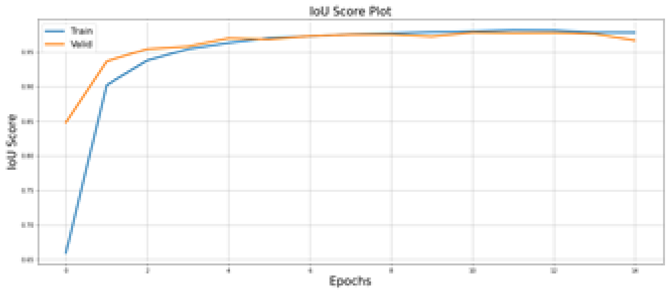


Figure 7: DeepLab IoU scores

The results of this comparative evaluation highlight the superiority of the U-Net model in automatic polyp segmentation within colonoscopic frames. U-Net's exceptionally high Mean IoU Score and low Mean Dice

Loss signify its accuracy and robustness in this medical image segmentation task. The consistent performance across the test data, both in terms of Dice loss and IoU scores, further underlines the model's reliability.

Conversely, DeepLab, while showing good performance, falls slightly behind U-Net in Mean IoU Score and exhibits more variability in segmentation results. The variability in Dice loss and IoU scores for DeepLab suggests that it may be more sensitive to certain factors or conditions in the data.

The statistical significance of the performance difference between U-Net and DeepLab should be explored through further analysis. Additionally, fine-tuning and optimization of the models could potentially improve the performance of DeepLab.

These findings contribute to the advancement of computer-aided diagnosis systems for colorectal diseases. The high accuracy and robustness of U-Net make it a compelling choice for the detection of polyps in colonoscopy videos, potentially leading to more accurate and efficient early diagnosis and treatment of colorectal diseases. Further research can focus on refining and adapting these models to real clinical scenarios, moving us closer to improved patient outcomes in the context of colorectal disease diagnosis and treatment.

IV. CONCLUSION

In the realm of medical image segmentation, the accurate detection of polyps in colonoscopy videos holds paramount importance for early diagnosis and the treatment of colorectal diseases. This study presented a comparative evaluation of two state-of-the-art deep learning models, U-Net and DeepLab, for the automatic segmentation of polyps in colonoscopic frames using the CVC-ClinicDB dataset.

The CVC-ClinicDB dataset, with its diverse collection of colonoscopy images, provided a robust foundation for this comparative analysis. The primary evaluation metric, Mean Intersection over Union (IoU), along with Mean Dice Loss, allowed for a comprehensive comparison of the models' performance.

U-Net exhibited superior performance in this task, achieving an impressive Mean IoU Score of 0.9897 and a relatively low Mean Dice Loss of 0.0523. The consistent Dice loss and high IoU scores across the test data demonstrated remarkable accuracy and robustness in polyp segmentation. These results underline U-Net's compelling potential for clinical application.

Conversely, DeepLab, though respectable, presented a slightly lower Mean IoU Score of 0.9676 and a marginally higher Mean Dice Loss of 0.0417. The variations in Dice loss and IoU scores indicated a level of sensitivity in DeepLab's performance, particularly in certain cases. While DeepLab showcased good segmentation results, it was outperformed by U-Net in this specific task.

In conclusion, our comparative analysis reveals that the U-Net model outperforms DeepLab in automatic polyp segmentation in colonoscopic frames using the CVC-ClinicDB dataset. The exceptionally high Mean IoU Score and low Mean Dice Loss for U-Net signify its accuracy and robustness in this medical image segmentation task, making it a compelling choice for the detection of polyps in colonoscopy videos.

These findings contribute to the advancement of computer-aided diagnosis systems for colorectal diseases, potentially improving patient outcomes through early and precise polyp detection. As the field of medical image segmentation continues to evolve, further research and development in this area can potentially refine and adapt these models for real clinical scenarios, bridging the gap between cutting-edge technology and improved healthcare outcomes.

V. REFERENCES

[1] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR) (pp. 770-778).

[2] Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2018). DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4), 834-848.

[3] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI) (pp. 234-241).

[4] Silva, S., & Marques, J. S. (2018). Polyp Segmentation in Colonoscopy Images: A Constrained Deep Learning Approach. IEEE Transactions on Medical Imaging, 37(11), 2483-2493.

[5] Fernández-Esparrach, G., Bernal, J., López-Cerón, M., Córdova, H., Sánchez-Montes, C., Rodríguez de Miguel, C., ... & Ayala, G. F. (2017). Exploring the Clinical Potential of an Automatic Colonic Polyp Detection Tool in Colonoscopy. Endoscopy, 49(06), 556-563.

[6] Cai, S. L., Yao, Y. Q., Cao, S. K., Liu, L. R., Zhang, Y. F., Sun, J. J., ... & Chen, G. (2020). Application of deep learning in gastrointestinal imaging: Interpretation of the major findings in the National Polyp Study (NPS) dataset. European Radiology, 30(1), 61-68.

[7] Li, L., Zeng, X., Jin, X., Lu, L., Zhang, H., & Niu, L. (2021). Deep learning in video-based colonoscopy for polyp detection: A systematic review and meta-analysis. Endoscopy International Open, 9(06), E746-E755.

[8] Mahmood, T., Niazi, T., & Jahanzaib, M. (2019). Polyp detection in colonoscopy images using deep convolutional neural networks. Biomedical Signal Processing and Control, 47, 114-126.

[9] Urban, G., Tripathi, P., Alkayali, T., Mittal, M., Jalali, F., Karnes, W., ... & Wong, J. (2018). Deep learning localizes and identifies polyps in real time with 96% accuracy in screening colonoscopy. Gastroenterology, 155(4), 1069-1078.

[10] Mori, Y., Kudo, S. E., Chiu, P. W., Singh, R., Min, M., & Shimura, T. (2018). Impact of an automated system for endocytoscopic diagnosis of small colorectal lesions: An international web-based study. Endoscopy, 50(9), 915-925.

[11] Bernal, J., Sánchez, F. J., Fernández-Esparrach, G., Gil, D., Rodríguez, C., & Vilariño, F. (2015). WM-DOVA maps for accurate polyp highlighting in colonoscopy: Validation vs. saliency maps from physicians. Computerized Medical Imaging and Graphics, 43, 99-111.

Cite this article as :

Chandrakantha T S, Basavaraj N Jagadale, "Comparative Analysis of U-Net and DeepLab for Automatic Polyp Segmentation in Colonoscopic Frames Using CVC-ClinicDB Dataset", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Online ISSN : 2394-4099, Print ISSN : 2395-1990, Volume 10 Issue 5, pp. 263-269, September-October 2023. Available at doi : https://doi.org/10.32628/IJSRSET2310550

Journal URL : https://ijsrset.com/IJSRSET2310550