IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Automatic Detection of Polyps Using UNet

K. Nikita [1], L. Kusuma [2], Sanjana Das [3]

Department of Computer Science and Engineering
Vardhaman College Of Engineering
Hyderabad, India

Dr. H. Venkateswara Reddy
Professor
Department of Computer Science and Engineering
Vardhaman College Of Engineering
Hyderabad, India

ABSTRACT

One of the most prevalent forms of malignant cancer is colon cancer. It begins to develop as a polyp, which is essentially an outgrowth from the surface of the colon. Therefore, one of the main purposes of endoscopy and colonoscopy is the early detection of polyps and malignancies. In order to dramatically increase the robustness and efficacy of colorectal cancer screening, as well as improve segmentation, accuracy, lesion detectability, and histological characterization accuracy, DCNN (deep convolutional neural networks) techniques based on U-Net architecture are applied. Data augmentation is utilised to expand our dataset, giving U-Net access to extra details that lead to accurate detection. The presence of polyps is not consistent, the colour pattern is not uniform, and there is a reflection effect in photos of polyps taken during colonoscopy and endoscopy. Over and under segmentation may result from this. The segmentation method is based on a model of a polyp's presence, which is defined as a noticeable shape enclosed within a polyp. This model takes these elements into consideration. An area can be recognised by the presence of edges and valleys. Post-processing techniques including morphological changes to soften segmentation boundaries and grouping neighbouring objects that originally belonged to a large polyp in the output segmentation chart are used to increase the accuracy of polyp detection. Polyp and non-polyp instances are separated for each pixel. The clinician can now identify the polyp with greater ease, speed, and accuracy. In the development of a CAD (Computer-Aided Diagnosis) system, automated polyp segmentation can be useful. Therefore, we propose an effective U-Net strategy for DCNN design and method for automated polyp detection.

Keywords: Colorectal cancer, polyp, DCNN, U-Net, post-processing, segmentation, augmentation.

I. INTRODUCTION

One of the most prevalent malignant cancers, colon cancer is also the second leading cause of death from cancer. Since colorectal cancer can be treated in its initial stages, early detection and localization of polyps are crucial to the disease's management. Polyps, which are essentially a protrusion from the surface of the colon, are the first stage of colorectal cancer and develop through a series of changes before becoming a serious condition. Because early polyp diagnosis improves a patient's prognosis, it is one of the main goals of endoscopy and colonoscopy. Endoscopy is a procedure that entails introducing a long, flexible tube with a camera inside the body through a tiny incision or a natural hole like the mouth or anus to closely examine an internal organ or tissue.

Polyp Segmentation:
Images of colonoscopies extracted from documentaries on actual interventions. While watching the movies, we realised that the illumination of the probe would provide us with hints regarding the presence of a polyp in a photograph. Segmentation is a key enabling technology for medical image analysis using a wide range of approaches. The interpretation of colonoscopy images, which includes polyp segmentation, is a challenging task because of inherent picture appearance and polyp morphology variations. Variations in polyp size, shape, and appearance cause polyp features to alter at various phases of growth. Initially, colorectal polyps

frequently have tiny sizes and few distinctive features. Therefore, at this point, there is a possibility to avoid them for other intestinal folds and wrinkly structures.

II. LITERATURE SURVEY

Mahmud et al. [1] proposed PolypSegNet uses multiple sequential depth dilation initiation (DDI) blocks, a deep fusion skip module (DFSM), and a deep reconstruction module (DRM) to extract polyps from colonoscopy images. Generate automatically. SegNet architecture modified for segmentation. Fan et al. [2] In order to improve an FCN-like model for medical picture segmentation, we suggest PraNet, which uses parallel partial decoding and reverse attention modules. UNet is suggested as an alternative to the classic FCN (Fully Convolutional Network) architecture's single encoder, which significantly boosts FCN's speed and has become a popular option for medical image segmentation. The features from the encoding and decoding layers are concatenated using skip connections in the encoder-decoder-based structure known as UNet. A number of variations that were suggested for polyp segmentation and produced encouraging results were motivated by UNet's performance. Jha et al. [3] provided Double UNet, a UNet combination. A pre-trained VGG-19 serves as the foundation of the first UNet. To effectively collect more semantic data, the second UNet is added below the first UNet. Additionally, they use Atrous Spatial Pyramid Pooling (ASPP) to gather contextual data from the network. Kang and Gwak [4] employed Mask-RCNN as the main framework for automatic polyp detection and segmentation, that is based on ResNet50 and ResNet101. Using a fully convolutional neural network (FCN), pixel-level segmentation was achieved. Zhou et al. [5] introduced UNet++, a highly supervised encoder-decoder network that joins UNet together using several layered, dense skip routes. Zhang et al. [6] employed the FCN-8S to divide potential polyp area candidates into discrete regions, and a random forest classifier used the texton characteristics computed from each region to make the final determination.

III. EXISTING SYSTEM

There have been several different ways proposed for accurate polyp segmentation. Deep learning approaches and conventional machine learning techniques can be used to broadly categorise the existing research on polyp segmentation. The polyp's edge or its colour and texture are both examined by the processing segmentation methods for polyp segmentation. Polyp segmentation research is becoming more developed. Researchers are using a range of methods to conduct precision polyp segmentation experiments. The dearth of research that employ the cross-dataset test to assess the generalizability of models, however, remains the core problem in the field. Most recent studies have suggested strategies that have been evaluated on discrete, frequently small, unbalanced, and particularly hand-selected datasets. Furthermore, many troublesome polyps are commonly missed during colonoscopy exams and if they are not detected in time, they can develop into cancer. Additionally, there are significant obstacles in the medical profession because to the lack of sizeable training datasets and the frequent imbalance in the obtained datasets. These problems make it more challenging to build trustworthy and portable methods for precise polyp segmentation. In this study, we want to address these problems by developing an algorithm that might achieve high performance.

LIMITATIONS OF EXISTING SYSTEM:

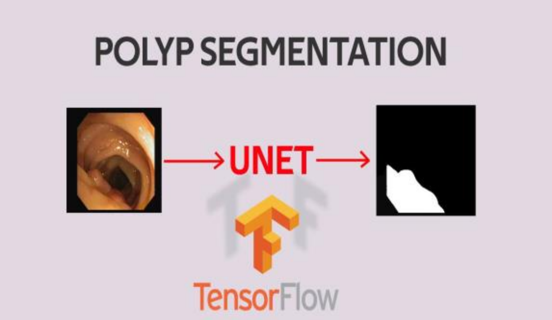
- Automatic polyp detection is challenging due to the significant differences between polyps and their analogues.
- Convolutional neural networks are the foundation of contemporary methods (CNNs).
- But given the lack of training data, they might not be successful, resulting in numerous missed detections and false positives (FPs).
- Some of the CNN architectures used by the current models include Alex Net, Mask R-CNN, and Google Net.

IV. PROPOSED SYSTEM

The primary goal of our suggested model is to increase the precision of polyp detection. In order to increase the robustness and efficacy of colorectal cancer screening as well as improve segmentation accuracy, our suggested model leverages DCNN techniques based on U-Net architecture. We employed data augmentation to expand our dataset, giving U-Net access to more details that lead to more precise detection. Convolutional neural networks like U-Net were created specifically for the purpose of segmenting biological images. A more exact segmentation with fewer training images is now possible thanks to extended and upgraded network architecture. With the help of complex deep convolutional neural network construction approaches and U-Net methodology, we successfully combine the two to present a method for automatically detecting polyps in this thesis. We examined advanced techniques and algorithms that are crucial to creating a highly effective U-Net.

BASIC CONCEPTS:

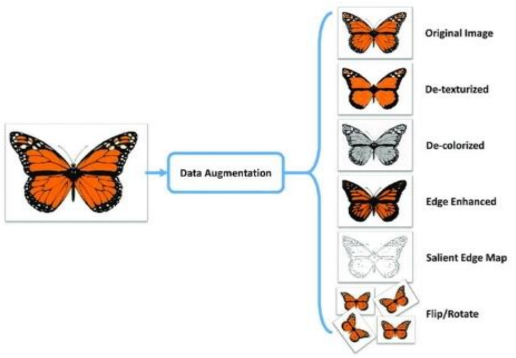
Deep Learning: Artificial intelligence (AI) systems are created using a machine learning technique known as deep learning. It is based on the concept of artificial neural networks (ANN), which are created to carry out complicated analysis on massive volumes of data by directing them via numerous layers of neurons.



UNET: U-Net is a CNN which was developed for the purpose of segmenting biological pictures. The networks architecture was improved and expanded to allow for more precise segmentation with fewer training images. Segmentation of a 512x512 picture takes not more than a second on a present-day GPU.

DCNN: The layering of DCNNs is what gives them their power. A DCNN processes the red, green, and blue components of the image simultaneously using a three-dimensional neural network. Compared to conventional feed forward neural networks, this significantly lowers the quantity of artificial neurons needed to process an image. Images are fed into deep convolutional neural networks, which then use the data to train a classifier. Instead of matrix multiplication, the network uses a particular mathematical process called "convolution."

Data Augmentation: Data Augmentation is one method of preventing over fitting when training datasets are insufficient. Over-fitting occurs when a model learns patterns from insufficient training data that do not transfer to fresh data, or when the model begins to forecast based on irrelevant characteristics.

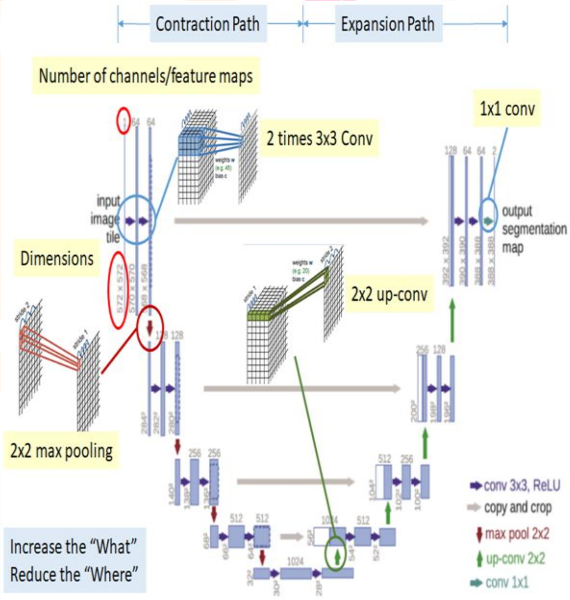


In this work, we enhance our training data set via data augmentation techniques. Consider a training set with 100 photos of polyps and non-polyps. Rotating, mirroring, moving, zooming, and altering contrast, among other things, may produce around 2000 different pictures. Data augmentation from a single polyp image to 10 additional photos is illustrated below using random rotation, flipping, shifting, and zooming processes. Data augmentation is used in a variety of machine learning applications to aid in the building of more accurate models.

Convolution Operation: Convolutional process in mathematics, convolution is a technique that takes two functions and yields a third function that describes how the shape of one function is changed by another. The way we analyse a variety of metrics and optimise our results by focusing on the closest ones is more like a convolutional operation than CNN. As a result, we develop new metrics that are weighted averages of the old ones, where the closest metrics are given more weight than the older ones.

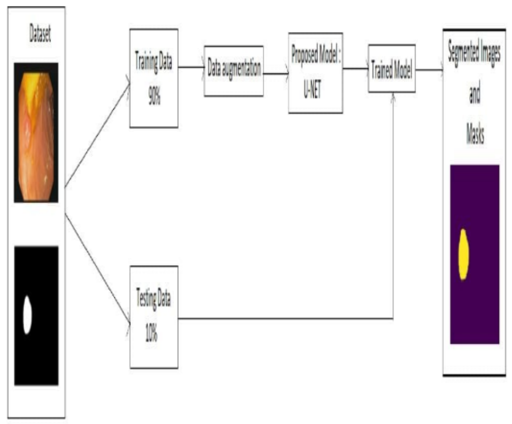
Pooling: Based on the outputs of the prior layer at a certain point, a pooling process creates an image. Within a rectangular area, the max pooling approach yields the highest value. The picture's brightest pixels are chosen using max pooling. When we are only interested in the image's brighter pixels and the image's background is dark, it is advantageous. The pooling layer may lower the feature representation's resolution, the quantity of parameters, and the amount of computation needed. It helps to prevent overfitting in several different ways. A pooling layer is frequently used in deep CNNs between subsequent convolutional layers.

V. SYSTEM ARCHITECTURE



In the architecture, operations are carried out in several convolutional layers. In order to help activate the neurons in a convolutional network, the architecture makes use of the Relu activation function. In order to lower the loss/cost function, it additionally employs Adam optimizer. The difference between the predicted and actual output is defined by the lost function. Therefore, by using various convolutions, or techniques in the convolutional network, our model is suggested to reduce the loss or error. Additionally, it employs pooling techniques to cut down on the quantity of network computations and parameters that must be learned.

VI. SYSTEM BLOCK DIAGRAM:



- Initially, the dataset is read by the system, later divided into train dataset. We will train the model in prior which results in training data.
- The trained data then undergoes data augmentation, where the images are rotated in several ways and angels from which the model gets numerous images from a single image.
- It performs several convolutions of U-Net architecture
- Processing through all layers of U-Net architecture, the trained model is proposed. We test the model with the testing data.
- The output of the testing data will give the accuracy of the model.

VII. CONCLUSION

The major objective of our proposed model is to improve the accuracy of polyp detection. The robustness and efficacy of colorectal cancer screening as well as segmentation precision may be significantly improved by applying the DCNN techniques based on U-Net architecture to our recommended model. The output of the model results in terms of IOU score and Dice loss. IoU score is the area of union between the predicted segmentation and the ground truth divided by the area of overlap between the predicted segmentation and the latter. The imbalance between foreground and background is addressed by dice loss, but it ignores another imbalance between easy and difficult examples that has a similar negative impact on a learning model's training process.

```
Evaluation on Test Data:
Mean IoU Score: 0.9823
Mean Dice Loss: 0.0430
```

VIII. FUTURE WORK

Images from colonoscopies are used to recognise polyps. Therefore, more medical datasets must be gathered to revise, refine, and corroborate the findings. Additionally, improve the suggested framework further so that it can recognise all future polyp morphological varieties. We only evaluated the U-Net model, therefore it might be beneficial to incorporate more pre-trained models and frameworks in the future, such as Google Net or a hybrid RESNET and U-Net architecture, to improve performance and strengthen its generalising powers.

IX. REFERENCES

[1]T.Mahmud, B. Paul, and S. A. Fattah, “PolypSegNet: A modified encoder-decoder T architecture for automated polyp segmentation from colonoscopy images,’’ Comput. Biol. Med., vol. 128, Jan. 2021, Art. no. 104119.

[2] D.-P. Fan, G.-P. Ji, T. Zhou, G. Chen, H. Fu, J. Shen, and L. Shao, ‘‘PraNet:Parallel reverse attention network for polyp segmentation,’’ in Proc. Int.Conf. Med. Image Comput. Comput.-Assist. Intervent. Cham, Switzerland: Springer, 2020, pp. 263–273.

[3] D. Jha, M. A. Riegler, D. Johansen, P. Halvorsen, and H. D. Johansen, ‘‘DoubleU-Net: A deep convolutional neural network for medical image segmentation,’’ in Proc. IEEE 33rd Int. Symp. Comput.-Based Med. Syst. (CBMS), Jul. 2020, pp. 558–564.

[4] J. Kang and J. Gwak, ‘‘Ensemble of instance segmentation models for polyp segmentation in colonoscopy images,’’ IEEE Access, vol. 7, pp. 26440–26447, 2019.

[5] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, ‘‘UNet++: A nested U-Net architecture for medical image segmentation,’’ in Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support. Cham, Switzerland: Springer, 2018, pp. 3–11

[6] L. Zhang, S. Dolwani, and X. Ye, ‘‘Automated polyp segmentation in colonoscopy frames using fully convolutional neural network and textons,’’ in Proc. Annu. Conf. Med. Image Understand. Anal. Cham, Switzerland: Springer, 2017, pp. 707–717.

[7] Yu L, H. Chen, Q. Dou, J. Qin, and P.A. Heng, Integrating online and offline three-dimensional deep learning for automated polyp detection in colonoscopy videos," IEEE Journal of Biomedical and Health Informatics, vol.21, pp.6575, January 2017.

[8] O. Bardi, D.S.Sosa, B.G.Zapirain and A.Elmaghrby, "Automatic colon polyp detection using convolutional encoder-decoder model, "2017 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), pp.445448, 2017

[9] W. T.Xiao, L.J. Chang, and W.M. Liu, "Semantic segmentation of colorectal polyps with deep lab and LSTM networks, "2018 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW), pp.12, 2018.

[10] G. Urban, P. Tripathi, T. Alkayali, M. Mittal, F. Jalali, W. Karnes, and P. Baldi, "Deep learning localizes and identifies polyps in real- time with 96% accuracy in screening colonoscopy,Gastroenterology, pp.1069 1078,2018.

[11] F. Bray, A. Jemal, R.A. Smith et al, Global cancer transactions according to the human development index (2008-2030): a population-based study, Lancet Oncol, Vol.13, pp.790801, 2012.

[12] Y. Shin, H. A. Qadir, L. Aabakken, J. Bergsland, and I. Balasing- ham, "Automatic colon polyp detection using region-based deep CNN and post-learning approaches," IEEE Access, vol. 6, pp. 4095040962, 20185.