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Exponential Chef based Optimization Enabled Deep Learning for Polyp Frame Detection and Polyp Segmentation using Colonoscopy Videos

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A B S T R A C T

Identifying and describing the abnormal develop ment of tissues as they appear in medical frame images of endoscopy or colonoscopy is known as polyp segmentation. Accuracy of Polyp segmentation depends on high-quality imaging data, which may not always be available resulting in misiden tification and compromisation in segmentation precision. The most effective method of detecting colorectal cancer is still a colonoscopy. Nonetheless, notable miss rates for polyps have been seen, especially in cases with many tiny adenomas. This offers a chance to make use of computer-aided technologies to assist physicians in their work and lower the amount of polyps overlooked .In order to address these issues the Exponential chef-based optimization (ECBO) algorithm is introduced as it will help to train the Deep Maxout Network and Lightweight TransUNet weights to increase the accuracy of segmenting polyps from video frames. We first collect the thousand-frame image dataset known as (KVasir-SEG), and we preprocess the data by using Adaptive median filter with CLAHE i.e. Contrast Limit adaptive histogram equalization (CLAHE). CLAHE enhances local contrast, making the image more suitable for subsequent processing like edge preservation by the adaptive median filter also Adaptive median filtering can effectively reduces the noise. On the KVasir-SEG dataset, A polyp frame detection is carried out by Deep-Maxout Network. The experimental results show that ECBO based Lightweight TransUNet performs better than earlier methods in terms of Dice, Interception over union (IoU), Recall, and Precision. These results demonstrate the strong gen eralization strength and learning capability of the proposed that ECBO based Lightweight TransUNet approach, which makes it a desirable substitute for real-world applications with large data variations.

1. INTRODUCTION

A polyp is an a typical cellular clump that develops on the inside surface of the colon. Neoplastic and nonneoplastic polyps are the two different kinds of polyps. Nonneoplas tic polyps include those that are hamartomatous. Neoplastic polyps are tumors that have irregular shapes [1]. Neoplastic polyps are irregular growths in the colon that have the potential to develop into cancer. These tumors may be malignant if their microscopic form is used to classify them. The identification and excision of malignant polyps is an essential part of tumor therapy [2]. Colon cancer may eventually arise from some polyps. Unusual polyps that emerge from the intestinal epidermal lymphatic system are the source of colon cancer. The main technique for locating and eliminating polyps is through surgical procedures, which greatly lower the risk of lung Cancer. Adopting deep learning-based automatic tech niques has resulted in notable advancements in recent years. Certain approaches combine deep learning with conventional methods. Certain techniques are employed in certain methods [1] ,to identify image patches exhibiting polyps, and subse quently classify such patches using deep learning into ”without polyps” and ”with polyps” groups [2]. Artificial intelligence (AI) methods have been used recently to help doctors automat ically identify candidate lesion polyps during colonoscopies. However, there are still two issues that make creating AI models with a good detection rate difficult: Limited data with annotations. Deep learning models frequently have an insa tiable appetite for large-scale, heavily labeled video datasets. Additionally, there isn't a community-accepted standard to assess the techniques for real Performance with Dynamic complexity [3]. Increased polyp identification rates have been suggested by deep learning approaches to polyp detection. Nevertheless, most of these systems are created and assessed using static colonoscopy pictures, whereas actual therapy is carried out using a real-time video stream. In contrast to carefully chosen photos, non-curated video data contains a higher percentage of low-quality frames, but it also contains temporal information that can be utilized to make predictions that are more reliable [7]. The rapidly changing computer technologies has led to a significant attention be Convolutional Neural Networks (CNNs) in the field of ”deep learning”[2]. These networks have demonstrated breakthroughs not only in biomedical applications like gland segmentation,cell classifi cation and robotic tool detection etc but also in natural image analysis [8]. In colorectal image analysis, Due to the inherent picture quality and variations in morphology across individual polyps [4] segmentation becomes crucial and challenging task. Polyps' characteristics show variation in size, shape, and ap pearance throughout different stages of growth. A colonoscopy involves using an endoscope with a tiny camera on the angle so that to visually inspect the gastrointestinal tract[5]. The polyps are found inside the intestines and removed right away during a visit. Human error can result in the examination losing polyps due to fatigue, inattention, or insensitivity to the appearance of the polyps [6]. The way in which polyps show in pictures during a colonoscopy is greatly affected by the imaging equipment and lighting employed during colonoscopy. Illumination variations and reflecting, localized prolonged exposure glows can cause significant frame picture differences [7]. Polyps are unable to have discernible tran sitions between them and surrounding tissues, and they can be easily identified even from significantly changed camera locations. Furthermore, considerable segmentation mistakes may be caused by extraneous artifacts such as blurred motion, blurring, or even medical equipment visible in the camera's perspective [8]. In order to improve polyp segmentation and identification for frame picture accuracy and efficiency for early diagnosis, we suggested a unique deep learning approach in this study called ECBO TransUNet.

2. RELATED WORK

ADLtechnique for quick polyp identification was presented in the study [9], and it can be integrated into a computer-aided diagnosis (CAD) system. The you-only-look-once (YOLOv3) architecture, on which this model was based, provided an ac ceptable trade-off between predicting time and efficiency. The research [10] proposed Dual-Tree Wavelet Pooled CNN (DT WpCNN), an enhanced Convolutional Neural Network (CNN) with a novel pooling method[26]. The resulting segmented mask contained some surplus high-intensity patches aside from the polyp area. The general effectiveness of CNN-based object detectors for polyp identification in colonoscopy videos was improved by the study [11]. Through the merging of the bidi rectional sequential data acquired in a sequence of edges, the false positive reduction unit utilized the temporal dependency of frame images in the video. A hybrid 2-dimensional/3 dimensional CNN architecture for polyp segmentation was presented in the study [12]. By including temporal and ge ographical correlations of calculations while preserving real time recognitions, the network enhanced polyp recognition. Extensive experiments proved that the hybrid method per formed better than the two-dimensional baseline. The proposed architecture was confirmed with patient films and the publicly available SUN polyp database.In the paper [13], a novel DLneural network was proposed. The network made use of a novel (UNet design) that includes fully three-dimensional layers, enabling it to receive streams of video in addition to multiple frame images. And there was an output layer that predicted dice. Using DL and classification features, the paper [14] suggested a coarse-to-fine segmentation framework for polyp segmentation. Next, the expected map was splited as simple and complex data.Utilizing a dual-classification method that is automated.A one-step procedure for recognizing polyps in colonoscopy frame images was reported in the research [15]. The semantic segmentation method made use of a fully CNN architecture. They then use transfer learning to locate and identify things. Michael

Yeung et al. [18] Focus U-Net This model was lightweight and accurate with the multiple datasets. Moreover, it was applicable to any image segmenta tion problem. This method produced the class imbalance issue. A. Haj-Manouchehri and Hossein Mahvash Mohammadi [19] uses Convolutional neural network. This method avoided the overfitting issues by utilizing the large data set for the training phase. The accuracy of the proposed system was very low if coloured images are used[13]. Ge-Peng et al. [20] proposed PNS+ in which Inference speed of this scheme was high. But was utilized only for polyp segmentation but it failed to utilize other closely related medical video analyses. NGOC QUANG NGUYEN et al. [21] proposed Multi-model deep encoder-decoder networks (MED-Net) This method accessed only a limited number of colon cancer databases. It was unsuccessful in applying to a real-time system. SONG-TOAN TRAN et al. [22] uses Modified Recurrent Residual Unet Network. This scheme reused the convolutional units that minimized network size. Applying models with a smaller size ensure the limited performance. Hemin Ali Qadir et al. [23] utilizes CNN able to detect the missed polyps and refine the detection output by incorporating some future frames[1]. It failed to learn extra features from video sequences, such as motion estimation and variability of polyp appearance within a sequence of frames[3]. Puyal et al.[24] proposed Hybrid 2D/3D CNN. This method was suitable in real-world clinical implementations of automated polyp detection[4]. It did not provide the better result with the large video datasets. Xiao Jia et al. [25] introduces Polyp Net (PLPNet). At inference time, PLPNet runs a forward pass convolutionally per mask prediction, thus coming free of cost for the polyp proposal stage and speeding up the inference. It did not provide the better result with the large video datasets[2]. Methodology: This part evaluates the performance of the ECBO TransUNet architecture for polyp segmentation; to prepare the data, we f irst gather the KVasir-SEG dataset . The general architecture of our proposed method is depicted in Figure 1. Preprocessing techniques for Image processing involves a vari ety of steps aimed at enhancing the quality and usability of the images for further analysis or applications. CLAHE improves local contrast and enhances details in images by redistributing intensity values.It adjusts the contrast enhancement locally, which is beneficial for images with varying illumination across different regions. Relatively straightforward to implement, especially with libraries available in popular programming languages. But suffers from Overamplification of Noise i.e. In regions with low contrast, CLAHE can amplify noise, leading to artifacts or unwanted enhancements. Processing time can be higher, especially for large images or in real-time applica tions. Adaptive median filter effectively reduces noise while preserving edges and details. By adding adaptive histogram equalization (CLAHE) and adaptive median filter for image preprocessing in deep learning can yield significant benefits in terms of enhanced contrast and noise reduction. Upsampling networks can effectively restore or enhance fine-grained spatial details in images that are lost during downscaling or earlier processing stages. Lightweight TransUNet [18] is used to extract significant features, such as GLCM texture features [21] involving Contrast, correlation, energy, and homogeneity, statistical features [20] involving mean, variance, skewness, LBP [22], LGXP [23] and SLIF [14] will be extracted, which will be trained using proposed ECBO algorithm.

3. STEPS IN PREPROCESSING

In early video segmentation techniques most popularly used segmentation method is Background Subtraction Method. In Background Subtraction Method first the Background is estimated and is subtracted from current frame. The difference between two is estimated as foreground that is the group of pixels that are rapidly changing are considered as foreground. The changed pixels are flagged for further processing

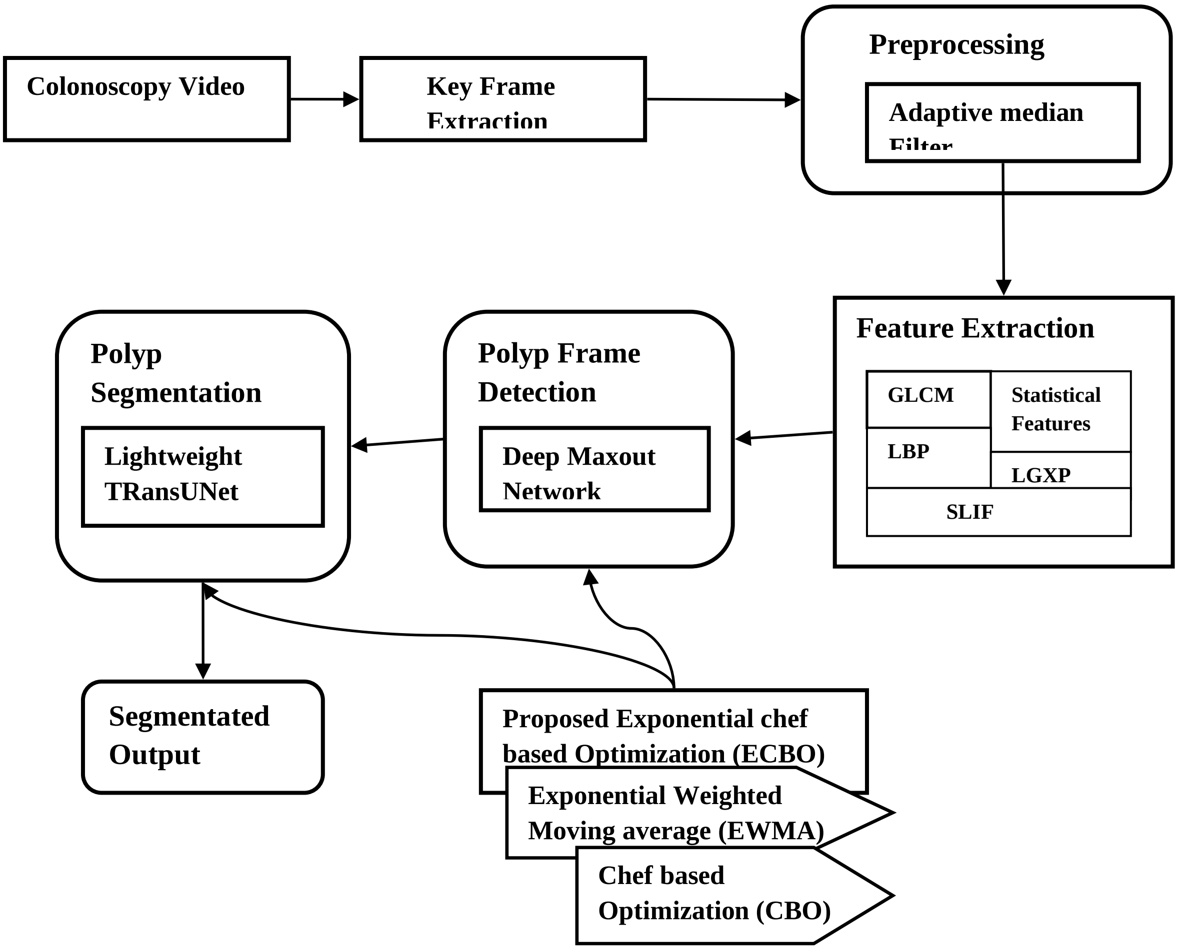


Fig. 1: The suggested methodology

A. Window Size Initialization & Histogram equalization.

1. Define an initial window size S_{min}
2. Typically, S_{min} is set to 3 (3x3 window).
3. For each tile Ti Calculate Histogram H_i
4. Compute the cumulative distribution function (CDF) from H_i
5. Transform the pixel values in T_i using

   $T_i eq(x,y)=CDF_i(I(x,y))$

B. Iterative Processing

1) For each pixel (x,y) in the image, increase the window size iteratively until a suitable median is found.

C. Steps within Each Iteration

1) Step A: Expand the window size.

2) Step B: For the current window size, find the median P_{med} of the pixel values within the window.

3) Step C: Calculate the local statistics

- $P_{(min)}$: Minimum pixel value in the window.
- $P_{(max)}$:Maximum pixel value in the window.
- $P_{(med)}$: median pixel value in the window.

- $P_{(mid)}$: Median of $P_{(min)}$, $P_{(max)}$, $P_{(med)}$
- Define a clip limit CL (typically a small value, like 0.01 or 0.02).
- Clip the histogram Hi such that no bin exceeds [CL×N] pixels in tile.
- Recompute the CDF and transform the pixel values again if necessary after clipping.

D. Perform checks

1) If $P_{(min)}$ P(med) $P_{(max)}$,the pixel (x,y)is likely not corrupted by noise, and $P_{(med)}$ is retained.

2) If $P_{(min)} \geq P_{(med)} \geq P_{(max)}$, replace P(med) with P(mid) .

3) If the window size reaches a maximum threshold, replace $P_{(med)}$ with $P_{(mid)}$

4) Combine the enhanced tiles back into the output image are enhanced using interpolation techniques to smooth the transitions between tiles.

The pre-processing output is clearly seen in figure 2 , in which enhancement in contrast and edges are clearly visible after removal of artifact.

Fig. 2: Sample Image after Preprocessing

4. POLYP FRAME DETECTION AND SEGMENTATION USING EXPONENTIAL CHEF-BASED OPTIMIZED LIGHTWEIGHT TRANSUNET

1. The primary goal is to define a suitable loss function that quantifies the difference between the predicted output and the ground truth. For tasks like image segmentation, where each pixel needs to be accurately classified or segmented, a common choice is the pixel-wise cross-entropy loss[9].

Let: Y ′ denote the predicted output (segmentation map) from the network.

Y denote the Ground Truth Segmentation map.

The pixel-wise Cross-Entropy Loss LCE is typically defined as[28]:

$$L_{CE}(Y', Y) = -\sum_{i,j} Y_{ij} \log(Y'_{ij}) \quad \textbf{(1)}$$

where Y_{ij} and Y'_{ij} are the ground truth and predicted values at pixel (i,j) respectively.

2. Network Output

The upsampling convolutional network transforms an input image X into the predicted segmentation map $Y' = f(X;\Theta.)$,

Where Θ. represents the parameters (weights and biases) of the network.

3. Optimization Objective The objective during training is to minimize the expected value of the objective function over a training dataset D.

$$\min_{\Theta} E_{(X,Y)\sim D}\,[L_{CE}\,(f(X;\Theta), Y)] \qquad (2)$$

4. Training Process During training, stochastic gradient descent (SGD) or its variants are typically employed to update the network parameters Θ .

The parameters are updated iteratively based on the gradients of the objective function with respect to Θ[31].

The update rule for SGD is:

$$\Theta \leftarrow \Theta - \eta \cdot \nabla_{\Theta} L_{CE}\,(f(X;\Theta), Y)$$

Where:

- η is the learning rate [11].
- ∇_{Θ} denotes the gradient of the objective function with respect to Θ .

5. Optimization with ECBO

To compute $\nabla_{\Theta} L_{CE}$,the backpropagation algorithm is used, which efficiently computes the Gradients of the objective function with respect to all parameters of the network by applying the chef rule The ”chef” strikes a balance between computational efficiency and accuracy by carefully choosing the most

pertinent input features (ingredients) from colonoscopy frames. Objective Function i.e the (Dish Quality Metric). An objective function evaluating the dish’s quality, quantifies segmentation accuracy. The ”chef” aims to

maximize this metric, such as Intersection over Union (IoU) or Dice coefficient. Chef is an optimization algorithm. Based on the dish quality measure, the ”chef” iteratively modifies the network’s parameters to improve

segmentation accuracy. This serves as the embodiment of the optimization method. The ”chef” continuously evaluates the network’s performance using validation data to make sure the model is effectively segmenting polyps.[41] Fast clinical application is made possible

by network optimization for real-time with designing a lightweight network i.e. network with less parameters. Objective function defines quality of dish. It depends on recipe i.e. Model, quality i.e. result Of segmentation. The

chef function aims to maximize the objective function i.e. to minimize loss function.[41]

$$O = \text{Evaluate}(R_t, I_t) = \text{Evaluate}(f(I_t, R), M_t)$$

The optimization algorithm adjust the model to improve quality of segmentation.

$$R = \text{Chef}(O,R)$$

5. PERFORMANCE METRICS FOR SEGMENTATION

1) **Accuracy** It is expressed as the ratio of all positive forecasts to True positives. It evaluates how effectively the model stays away from giving erroneous positive findings.[15]

$$\text{Accuracy} = \frac{TP + TN}{\text{Total Predictions}} \qquad (3)$$

2) **Precision** The proportion of accurate positive forecasts to all positive forecasts. It gauges how well the model can evade erroneous Positives.[8].

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

3) **Recall** It calculates the genuine positive rate or sensitivity. the proportion of true positives to all true positives plus false negatives. It assesses how well the model can recognize good examples.[4].

$$\text{Recall (Sensitivity)} = \frac{TP}{TP + FN} \quad (5)$$

4) **F1-Score** The precision and recall harmonic mean. A harmonic mean is calculated by adding up all of the reciprocals for each value in a dataset and dividing the total number of values .The value of the F1 score lies between 0 to 1 with 1 being a better [13]

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

6. RESULT

The Dice coefficient is the main statistic used in this section to evaluate polyp segmentation using the Kvasir-SEG dataset[5]. We further used recall, precision, and interception over union (IoU) paramaters.

Networks	Dice (%)	IoU (%)	Precision (%)	Recall (%)
A-DenseUNet [17]	90.85	86.15	97.66	94.48
PolySegNet [17]	88.72	82.86	92.54	91.68
CRF-RNN [17]	92.72	87.69	94.92	97.02
Lightweight TransUNet	94.30	93.76	95.91	98.04

TABLE I: Performance comparison of different networks.

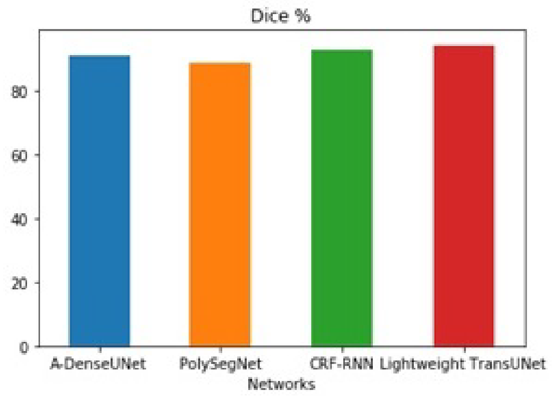
7. CONCLUSION

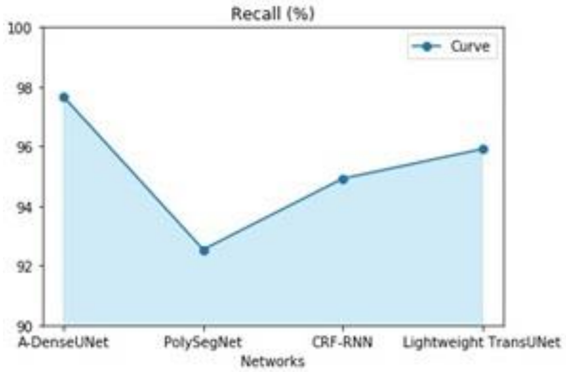
A workable solution to the polyp segmentation

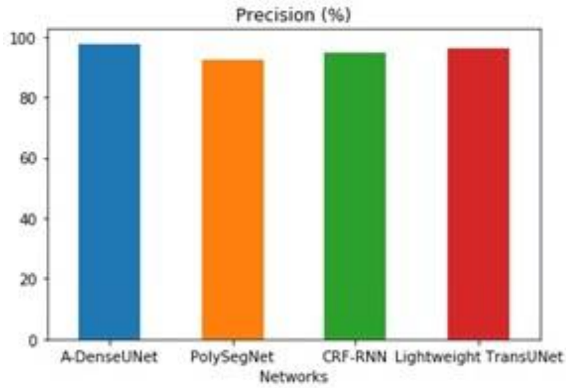
and identification issue in medical imaging data is provided by the proposed ECBO-Lightweight TransUNet. After gathering the KVasir-SEG dataset and using CLAHE and Adaptive

median filter for the preprocessing stage, the ECBO TransUNet performs better. The robustness, generalizability, and learning

capability of the ECBO TransUnet approach are demonstrated by these experimental results ECBO TransUNet's effectiveness on the KVasir-SEG dataset shows that it performs better than previous methods in terms of Dice (95.7 %), IOU (92.76 %), recall (98.04 %), and precision (96.91 %). Therefore, the proposed method has the potential to increase polyp segmentation efficiency, leading to better patient outcomes. Accuracy may be limited by the current polyp segmentation algorithms inability to withstand complex shapes and noise. In the future, advances in machine learning algorithms and computational approaches should improve segmentation accuracy, allowing for a better understanding of polyp's involvement in biological processes and prospective applications in a variety of sectors.







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