

Research Article

# Detection of Polyps Suspected of Colorectal Cancer in Endoscopy Images of Using a Network Based on Transformer

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## Abstract

Artificial intelligence (AI) has significantly impacted the healthcare sector, particularly in improving diagnostic and prognostic accuracy in medical imaging. This manuscript illustrates that AI integration can enhance polyp characterization accuracy, matching the proficiency of expert practitioners, and thereby reducing diagnostic errors and unnecessary interventions. By empowering general endoscopists with AI tools, underserved areas can ensure comprehensive patient care irrespective of medical expertise levels. The study focuses on developing an automated method for colon cancer categorization in colonoscopy images, leveraging a dataset from Kerman province and evaluating it against the publicly available ELSIVIER dataset. Employing deep learning techniques, specifically the Trans model, the research aims to detect and classify colonoscopy images into polyp-present and polyp-absent categories. The TransResU-Net architecture combines the strengths of residual networks, transformer blocks, and dilated convolutions, facilitating effective real-time polyp segmentation. Results show the model achieved a 98.90% accuracy on the private dataset, with a recall of 94.18% and an F1 score of 0.9641.

## Keywords

Colorectal Cancer, Colon Examination, Polyp Identification, Neural Networks, U-Net Model

## 1. Introduction

The healthcare sector continuously evolves, driven by technological advancements, with artificial intelligence (AI) be-

coming a key player. AI enhances diagnostic precision, treatment efficacy, and operational productivity. AI-driven diagnos-

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tic systems automate analysis of medical data, improving accuracy and efficiency, particularly in medical imaging, enabling better quality assessments [1]. These systems, essential in managing chronic diseases, utilize data from wearable devices to predict disease risks [2]. Machine learning, a subset of AI, enables systems to learn from data and recognize patterns, effectively performing tasks like anomaly detection and image recognition with minimal human input [3]. Specifically, machine learning and deep learning algorithms are crucial in analyzing CT and MRI scans, classifying findings to reduce unnecessary biopsies [4]. While AI shows promise in transforming healthcare outcomes and patient engagement, challenges remain regarding data needs, algorithm accuracy, interpretability, and ethical considerations. Furthermore, colorectal cancer's mortality rate is projected to increase significantly by 2030, highlighting the urgent need for improved diagnostics and treatments [5].

The main way to prevent CRC is to modify lifestyle, and the next best way is regular colon screening. Various diagnostic and prognostic methods for CRC screening include endoscopy, colonoscopy, blood tests, and stool tests [6]. Colonoscopy is considered the gold standard screening test for early detection and prevention of CRC-related cancer and mortality, and is the most widely used and effective invasive examination used to detect changes and search for and eliminate precancerous abnormalities in the large intestine (colon) and rectum. [7, 8]. Artificial intelligence (AI) technologies can speed up medical image analysis and help in the automatic diagnosis of colorectal cancer in its early stages, and can act as a complement and increase the survival rate of patients with cancer by up to 95% if diagnosed in the first 5 years of the disease, and have achieved promising results and help reduce skill gaps among doctors and consequently reduce the number of

lesions missed during colonoscopy [9, 10]. Therefore, the use of computer-aided systems for polyp detection is essential. In this study, we aim to introduce a computer-aided polyp detection system that will help to overcome the above problems. Deep learning is a major driver of the increasing use of artificial intelligence in a wide range of applications, including medical image analysis [11]. Deep learning approaches typically use a convolutional neural network (CNN) to extract relevant features. It is therefore essential that automated polyp detection has the highest possible sensitivity and accuracy to detect the most cases and avoid unnecessary treatment. [12, 13] Since artificial intelligence (AI)-based intelligent computer systems have been validated and widely used in medical imaging. A machine can act cognitively like humans, analyze, learn, and understand data, and AI-based models have the potential to help doctors diagnose, make predictions, and find accurate outcomes for treating patients [14]. In general, the goal of these studies can be described as follows: to provide an algorithm for polyp detection and classification, which can be divided into two main parts: First, in the manual database collection process, there is a lot of noise in each image, which deep learning algorithms struggle with in trying to classify and detect polyps [15]. When capturing images, the colonoscope lens rotates inside the intestinal tract to capture images of polyps from different angles. This rotational motion often leads to motion blur and reflection problems. This complicates the detection task by obscuring the boundaries of polyps [16, 17]. First, our goal is to remove noise and artifacts from each image and create a suitable image to feed the introduced algorithm. Second, we compare and verify the performance of the introduced algorithm using public ELSIVIER data and private data collected from patients.

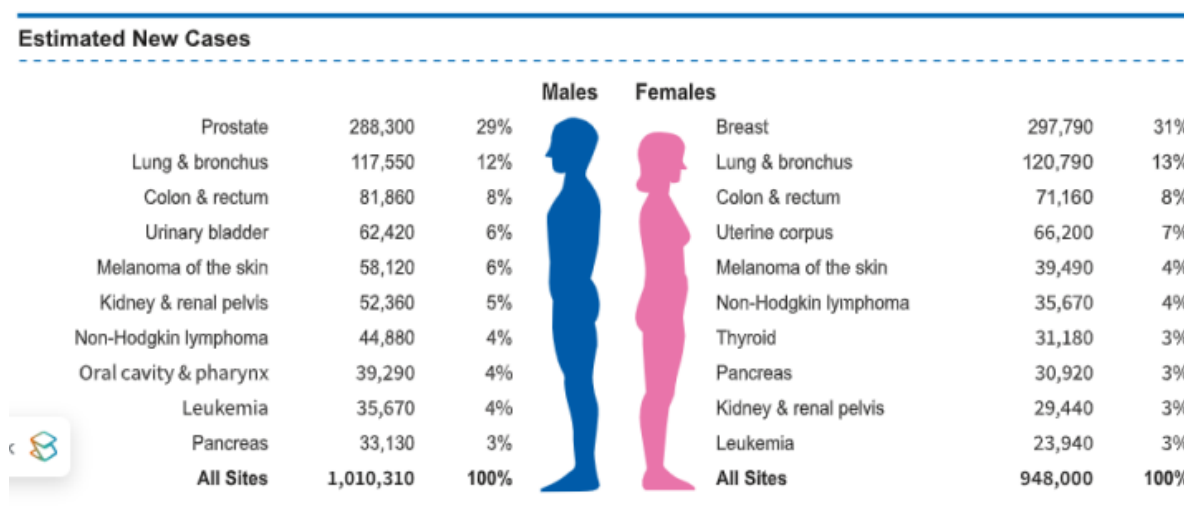
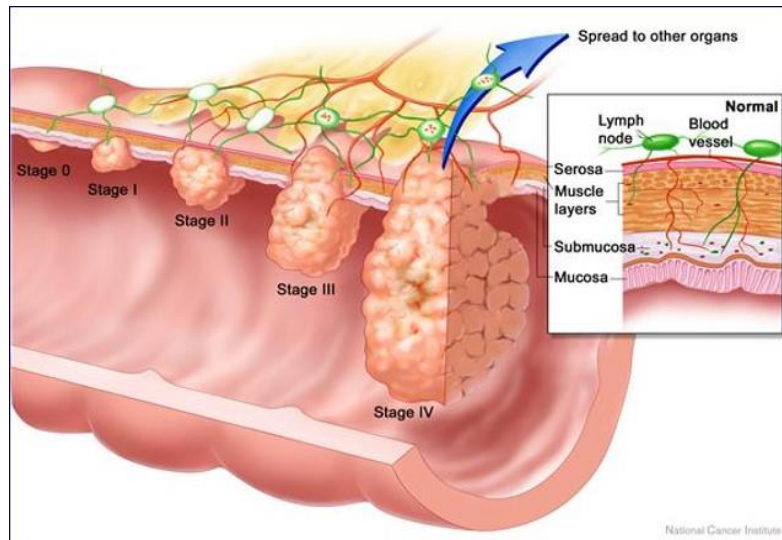


Figure 1. Distribution of new cases of the ten most common cancers in men and women worldwide [18].



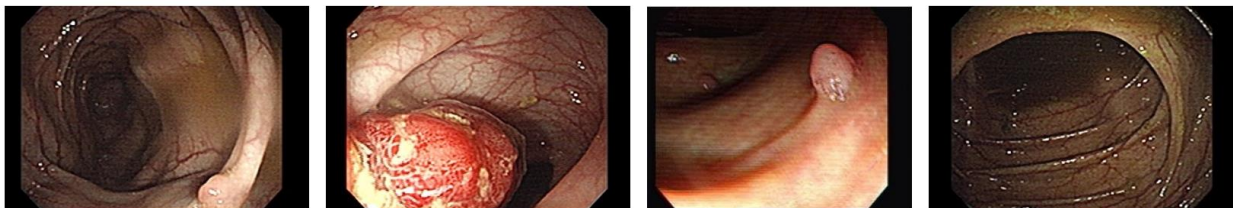
**Figure 2.** Different stages of bowel cancer [21].

Intestinal polyps, particularly those located in the colon, are identified through a range of diagnostic techniques aimed at detecting these growths within the large intestine [19, 20]. The selection of a specific diagnostic approach is often influenced by the patient's presenting symptoms, medical history, and the clinician's assessment [21, 22]. The primary methods employed for the diagnosis of intestinal polyps include colonoscopy, stool analysis, blood tests, and imaging modalities such as virtual colonoscopy (CT colonography), capsule endoscopy,

flexible sigmoidoscopy, and conventional CT scans. Computer-aided detection (CAD) systems aim to assist endoscopists by improving real-time detection, identification, and pathology prediction of colorectal polyps.

CAD systems primarily utilize deep learning models, especially convolutional neural networks (CNNs), trained on large colonoscopy image datasets to recognize polyp-related patterns.

## 2. Materials and Method



**Figure 3.** An example of a private data set collected.

Intestinal polyps, particularly those located in the colon, are identified through a range of diagnostic techniques aimed at detecting these growths within the large intestine. The selection of a specific diagnostic approach is often influenced by the patient's presenting symptoms, medical history, and the clinician's assessment. The primary methods employed for the diagnosis of intestinal polyps include colonoscopy, stool analysis, blood tests, and imaging modalities such as virtual colonoscopy (CT colonography), capsule endoscopy, flexible sigmoidoscopy, and conventional CT scans.

Current research highlights several prevalent challenges encountered by investigators in the development of algorithms for the detection of colorectal polyps utilizing colonoscopy

images. The construction of a colorectal polyp detection model that operates on colonoscopy-derived media presents numerous obstacles, which can be categorized into intrinsic and extrinsic issues. Intrinsic challenges pertain specifically to the detection model itself, such as the requirement for substantial computational resources to maximize polyp detection and the risk of overfitting due to data asymmetry. Conversely, extrinsic challenges encompass external factors, including inadequate bowel preparation and reflections from the light source used during colonoscopy, which may hinder the model's performance. Computer-aided detection (CAD) systems are designed to support endoscopists with the objective of enhancing the real-time detection, identification, and prediction of polyp

pathology, thereby minimizing the risk of overlooking or misdiagnosing colorectal lesions. These systems leverage deep learning models, particularly convolutional neural networks, which are trained on extensive datasets of colonoscopy images to identify patterns associated with polyps. The potential of these systems to improve diagnostic accuracy and efficiency

has garnered significant attention in the field.

The data was screened by specialist physician Dr. Nadia Bani Asad and her medical team at the Park Clinic private clinic, and images containing artifacts, blur, severe bleeding from the biopsy, bubbles in the intestine, and strong light reflection were reviewed and removed from the dataset.



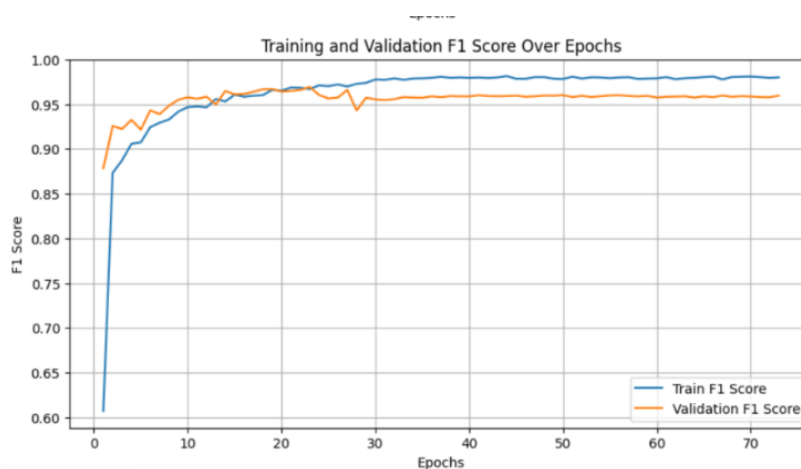
**Figure 4.** An example of missing and deleted samples from the dataset.

The RGB function in image processing plays a crucial role in the adjustment of color balance and the correction of image coloration. By manipulating the individual red, green, and blue channels, one can significantly enhance the overall visual quality of an image. This function facilitates precise control over the color attributes of an image, enabling adjustments in image channels and color correction, which contribute to a more natural and aesthetically pleasing appearance. A notable aspect of the RGB function is its capacity to achieve color balance, enhance visual appeal, and improve detail. Furthermore, preprocessing techniques that address issues such as contrast, noise, and sharpness allow clinicians to visualize and interpret images with greater efficacy. This enhancement not only leads to improved diagnostic outcomes but also promotes more efficient

and cost-effective healthcare delivery.

The highlights of this model are that TransResU-Net uses a combination of binary cross-entropy loss and dice loss for polyp segmentation in colonoscopy. Binary cross-entropy loss improves classification accuracy, while dice loss enhances segmentation quality, especially for unbalanced datasets. This dual approach optimizes both prediction accuracy and mask overlap, addressing a common challenge in medical image segmentation. The goal is to improve real-time polyp detection performance in colonoscopy images. It is worth noting that all models are trained with a set of meta-parameters, including loss functions, which highlight its effectiveness in segmentation and automatic polyp detection tasks.

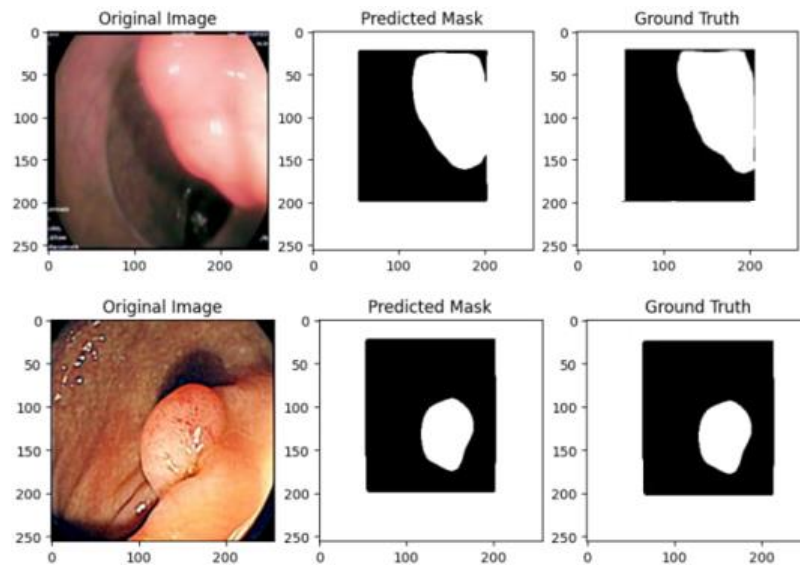
### 3. Result and Discussion



**Figure 5.** Training and evaluating the F1 score of the model on private data.

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els are trained with a set of meta-parameters, including loss functions, which highlight its effectiveness in segmentation and automatic polyp detection tasks. Avoiding overfitting and underfitting: Evaluation helps identify overfitting (when the model performs well on the training data but poorly on new data) and underfitting (when the model fails to capture the underlying structure of the data). A well-evaluated model strikes a balance between these extremes. After training, we evaluated the model on a test dataset to examine its performance metrics.



**Figure 6.** Sample predicted images of the model.

The evaluation of results is divided into two parts: the U-NET model's performance on the ELSIVIER database and the proposed model's evaluation on personal data. The U-NET model is preferred for polyp segmentation due to its superior performance. The effectiveness of the TransResU-Net architecture is quantitatively and qualitatively assessed across three databases, yielding an accuracy of 0.9890. The model's training indicates rapid convergence in accuracy and error, showcasing its strong segmentation ability for polyp images. Testing utilized a private dataset for colon cancer classification, complemented by Kvasir-SEG and BKAI-IGH datasets, ensuring diverse image representation. Data was split into 80% training, 10% validation, and 10% testing, with training spanning 200 epochs and implementing early stopping to mitigate overfitting. The Adam optimizer, with a learning rate of  $1e-4$  and batch size of 16, was employed, along with a combined loss function of binary cross-entropy and dice loss to enhance model accuracy and segmentation quality.

## 4. Conclusion

Convolutional neural networks (CNNs) demonstrate a capacity for processing extensive datasets in a manner akin to

human cognitive functions, thereby facilitating the advancement of advanced pattern recognition technologies that assist endoscopists in the real-time identification of pathologies. This thesis investigates a colon polyp detection methodology utilizing two distinct polyp datasets—one publicly available and the other privately collected—both of which are of sufficient size for analysis. The primary objective of this research is to evaluate the efficacy of the proposed method in detecting early indicators of colorectal cancer (CRC) with high accuracy and real-time processing capabilities, leveraging a novel real-world database. Additionally, the study aims to provide specialists with a reliable assessment of colon tissue and to minimize the adenoma detection rate (ADR) errors within the privately collected dataset.

The methodology outlined in this thesis is divided into three components. Initially, a private database was compiled, and the images were processed using various preprocessing techniques to prepare them for model training. This model comprises an encoder and decoder, each consisting of four blocks, with a pre-trained ResNet50 serving as the encoder and four corresponding decoder blocks. The input images are processed through the pre-trained encoder. The results indicate that the proposed approach exhibited superior performance in the segmentation and detection of intestinal polyps within the

privately collected database compared to the other two datasets. Evaluation metrics, including accuracy (AC), false negative rate (FNR), false positive rate (FPR), and overall accuracy, demonstrated that the proposed method achieved commendable performance across these criteria.

## Abbreviations

CNN Convolutional Neural Networks

## Conflicts of Interest

The authors declares no conflicts of interest.

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