IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

# A TWO STAGE METHOD FOR POLYP DETECTION IN COLONOSCOPY IMAGE

[1] Maheskumar V, [2] Santhoshkumar C, [3] Soundharajan S,[4] Vimalraj S
[1] Associate Professor, [2] Student, [3] Student, [4] Student
[1] Department of Computer Science Engineering,
[1]Paavai Engineering College, Namakkal, Tamilnadu, India.

***Abstract:*** Finding colorectal polyps, which are precursors to colorectal cancer, requires a colonoscopy. The possibility of automated polyp recognition in colonoscopy pictures to help gastroenterologists improve the efficiency and accuracy of their diagnoses has drawn a lot of attention. In this work, we suggest a brand-new, two-step procedure for polyp identification in colonoscopy pictures. We use a deep learning-based method for initial polyp localization in the first stage. The goal of convolutional neural networks (CNNs) is to improve efficiency by reducing the computing burden by focusing exclusively on areas with probable polyps. CNNs are trained on a huge dataset of annotated colonoscopy images to recognize regions of interest likely to stage.. To improve the accuracy of polyp detection, we conduct a more thorough study of the regions of interest found in the first stage in the second stage. To further describe the discovered regions of interest, we use sophisticated image processing techniques like texture analysis, shape recognition, and context-aware feature extraction. By decreasing false positives and raising overall detection accuracy, this step improves polyp detection's specificity. We experimented with a wide collection of colonoscopy pictures, including instances with different polyp types, sizes, and textures, to assess the effectiveness of our technique. When compared to other methods, our technique shows promising results in terms of both sensitivity and specificity. Additionally, the suggested two-stage architecture demonstrates resilience to noise, changes in lighting, and other typical difficulties.. In summary, the suggested two-step approach combines the advantages of deep learning-based initial localization with cutting-edge image processing techniques for refined identification, providing an efficient means of automated polyp detection in colonoscopy pictures. By improving the efficiency and accuracy of colorectal polyp detection, the integration of such automated technologies into clinical practice may ultimately improve patient outcomes for colorectal cancer screening and diagnosis.

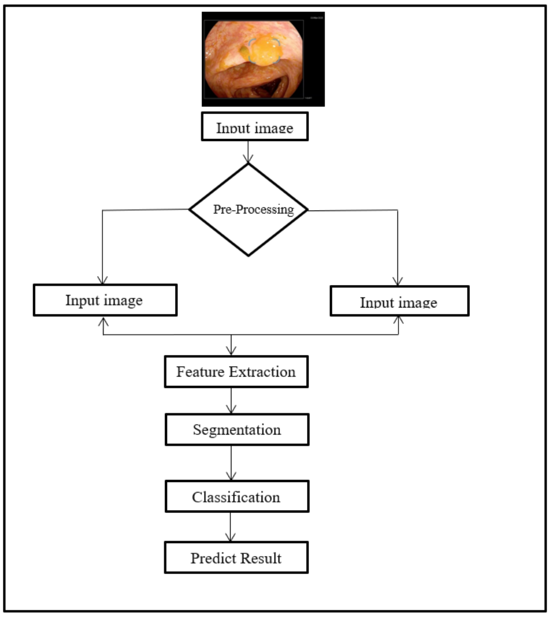
**Index Terms -** ColoRectal cancer (CRC), Convolutional Neural Networks (CNN), Sessile Serrated Adenoma/Polyp (SSAP), Discrete Cosine Transform (DCT), Pyramid Histogram of Oriented Gradient (PHOG)

## I. INTRODUCTION

The third most deadly type of cancer in the world, colorectal cancer (CRC), is also getting worse every day. Thus, prompt and precise diagnosis is necessary to preserve patients' lives. Polyps, which can be malignant or noncancerous, are the source of cancer. Therefore, the risky effects of cancer can be significantly decreased if the malignant polyps are appropriately identified and removed before they spread. The purpose of the colonoscopy is to look for colorectal polyps. However, skilled manual exams are prone to a variety of inaccuracies. As a result, several researchers have automated the diagnosing process using models based on deep learning and machine learning. Nevertheless, there are issues with gradient vanishing and overfitting with the current models. A deep learning model based on convolutional neural networks (CNNs) is suggested as a solution to these issues. First, the colonoscopy pictures are filtered and enhanced using guided image filter and dynamic histogram equalization techniques. After that, colorectal polyps from colonoscopy pictures are effectively detected and classified using the single shot multibox detector (ssd). Finally, the polyp classes are categorized using fully linked layers with dropouts. The suggested model performs noticeably better than the competing models, according to extensive experimental results on the benchmark dataset. One of the most deadly tumors worldwide, colorectal cancer (CRC) ranks third in India for cause of death among cancer-related fatalities worldwide.. It has been discovered that adenomas in colorectal patients develop due to hereditary or epigenetic factors. Endoscopic removal of colorectal polyps can lessen it. Pathology divides the polyps into four main groups: adenoma, sessile serrated adenoma/polyp (ssap), hyperplastic, which includes inflammation and juvenile polyps, and hyperplastic. There is a variable risk of cancer development in each of these groups. The likelihood of adenoma and ductal polyps developing into cancer is very high. Hyperplastic polyps, however, have a lower propensity to turn into cancer. .. Polyps less than 5 mm following resection may be skipped, per the preservation and use of beneficial endoscopic innovation (pivi) technique. Furthermore, because the hyperplastic polyps in the colon and rectum are benign, neither sample nor endoscopic excision are necessary. Therefore, a precise polyp classification can spare patients, medical professionals, and resources as well as a great deal of risk and labor. The majority of deep learning-based techniques for polyp detection and segmentation are solely tested and trained on the same center dataset using the WLE modality. The single-stage detection framework and the multi-stage detection framework are the two categories of object detection frameworks found in the literatureDeep learning techniques for segmentation can be broadly categorized into four types: pyramid-based, dilate convolution-based, encoder-decoder, and fully convolutional networks (FCN). Different groups have investigated each of these approach types in their localization and segmentation tasks of polyps. The Supplementary Notes' "Related work" section contains information on the methods used for both of these polyp activities. It is noteworthy that the majority of these approaches are supervised deep learning techniques, which suffer from a significant limitation in that they cannot generalize to data that has not been seen from a different center population or even from a different modality within the same center. The robustness is further compromised by the kind of endoscope that is being used. The test dataset is also made up of similarly obtained set data samples because the majority of the datasets available for method development only supplied selected image samples. Colonoscopy, like the majority of endoscopic procedures, involves using a camera and a light source to continuously visualize the mucosa. Live videos are captured during this procedure, and they are frequently tainted with pixel saturation, floating objects, excrement, and bubbles. The dynamics of the mucosal scene, such as occlusion, view-point shifts, and severe deformations, might significantly limit the performance of the algorithm. Therefore, it is crucial to conduct a more thorough cross-examination of the established algorithms' generalizability on a variety of data circumstances, such as continuous frame sequences and modality changes. These difficulties frequently cause medical image analysis techniques to fail. Imaging artifacts can result in either low accuracy or no detection of polyps, even with the current CNN-based approaches. Similarly, similar difficulties frequently cause algorithms to under- or over-segment areas for segmentation methods when exact boundary detection is crucial. This might impact automated therapy or resection operations, resulting in less-than-ideal treatment that promotes polyp recurrence.

## II. Deep Learning

Computational systems called CNNs are created specifically with pattern recognition in mind. CNN is involved in several industries, including healthcare, and plays a significant part in the diagnosis of photographs taken when a disease is still in its early stages. CNN outperforms human specialists in two tasks: image recognition and accurate diagnosis. Three different types of layers make up CNN: fully connected, pooling, and convolutional layers. Due to the fact that CNN employs a combination of technologies with these layers, it can handle images better than traditional networks and other networks like RNN. CNN's fundamental concept involves using two-dimensional images and two-dimensional filters, along with a learning transfer technique that involves training models using the best pretrained models and replacing the last three layers to determine the weights of the problem to be solved. Experts do not need to manually extract features because CNN features are extracted from the dataset they are trained on. CNN's capacity to pick up on the representative features in its training dataset is what makes it so strong. Convolutional layers function in a feedback loop similar to that of the human brain, with each layer providing input to the subsequent layer and so on until the desired features are acquired. One of three goals guides the development of colorectal polyp detection models: (1) polyp segmentation, (2) polyp detection, or (3) polyp categorization. Certain models are trained to perform many tasks concurrently, like segmentation or detection, then classification. Training photos with the associated labels are input to a network that learns how to localize a polyp in a particular image when a model is trained to detect polyps. The label format used for detection typically consists of four bounding box coordinates, a variable that indicates whether a polyp is present, and occasionally, if the dataset contains such information, the polyp's class. On the other hand, segmentation models are trained to surround an identified polyp with an image segmentation mask. The colonoscopy pictures are utilized to train segmentation models, and the accompanying image masks serve as the input labels. Ultimately, without disclosing the location, classification models are trained to categorize polyps according to the category to which they belong.




## III. Related Work

Promit Haldar [1] On the other hand, segmentation models are trained to surround an identified polyp with an image segmentation mask. The colonoscopy pictures are utilized to train segmentation models, and the accompanying image masks serve as the input labels. Ultimately, without disclosing the location, classification models are trained to categorize polyps according to the category to which they belong.

Pradipta Sasmal [2] A virtual biopsy technique is presented for colonic polyp categorization, which can determine the polyps' stage of malignancy. A polyp's shape, feel, and color provide enough clues about what kind of organism it is. The suggested framework uses pyramid histogram of oriented gradient (PHOG) information to describe the geometry or morphology of a polyp. An affine transformation-resistant fractal weighted local binary pattern (FWLBP) descriptor is used to capture the texture of the polyp surface. The local shape is represented by the PHOG features through the use of an oriented gradient histogram (HOG). An technique based on fuzzy entropy is used to choose significant features. For polyp classification, support vector machines (SVM) and RUSBoosted tree classifiers are employed. Using the K-fold cross-validation technique, over-fitting is prevented.. Additionally, it is somewhat resistant to changes in illumination, which are common during endoscopy. An algorithm for feature ranking based on fuzzy entropy is used to achieve the best possible feature fusion. Finally, RUSBoosted tree and kernel-based support vector machines (SVM) are employed to assess the suggested model's classification performance. It is evident from the experimental findings on two databases that the suggested strategy is applicable for the classification of colonoscopic polyps.

Ngoc-Quang Nguyen [3] Due to human error, a considerable number of polyps are overlooked during colonoscopies. Therefore, the primary driving force behind this work was the necessity to accurately and quickly diagnose polyps found in colonoscopy pictures. In this study, we offer a novel approach to polyp segmentation, based on the MED-Net architecture, which is a multi-model deep encoder-decoder network. By extracting discriminative features at various effective fields-of-view and several image scales, this architecture not only obtains multi-level contextual information, but it can also significantly improve prediction accuracy by upsampling. Additionally, it can capture polyp borders with greater accuracy thanks to the use of multi-scale effective decoders. Additionally, we offer a supplementary approach that enhances the segmentation performance of the system by combining an efficient weighted loss function with a boundary-aware data augmentation technique.

Ming Liu [4] Convolutional Neural Network (CNN)-based polyp detection has currently shown to be feasible by researchers; nevertheless, improved feature extractors are required to enhance detection performance. In this work, we examined the single shot detector (SSD) framework's potential for polyp detection in colonoscopy footage. SSD is a one-step process that creates a set of fixed-size bounding boxes for every item from various feature maps by using a feed-forward CNN. Three distinct feature extractors were evaluated: ResNet50, VGG16, and InceptionV3. ResNet50 and InceptionV3 were created with multi-scale feature maps embedded into SSD. Using a combination of multiple-size patches, they developed an SVM classifier that is more effective at identifying aberrant regions than one that just uses single-size patches.

## Methodology

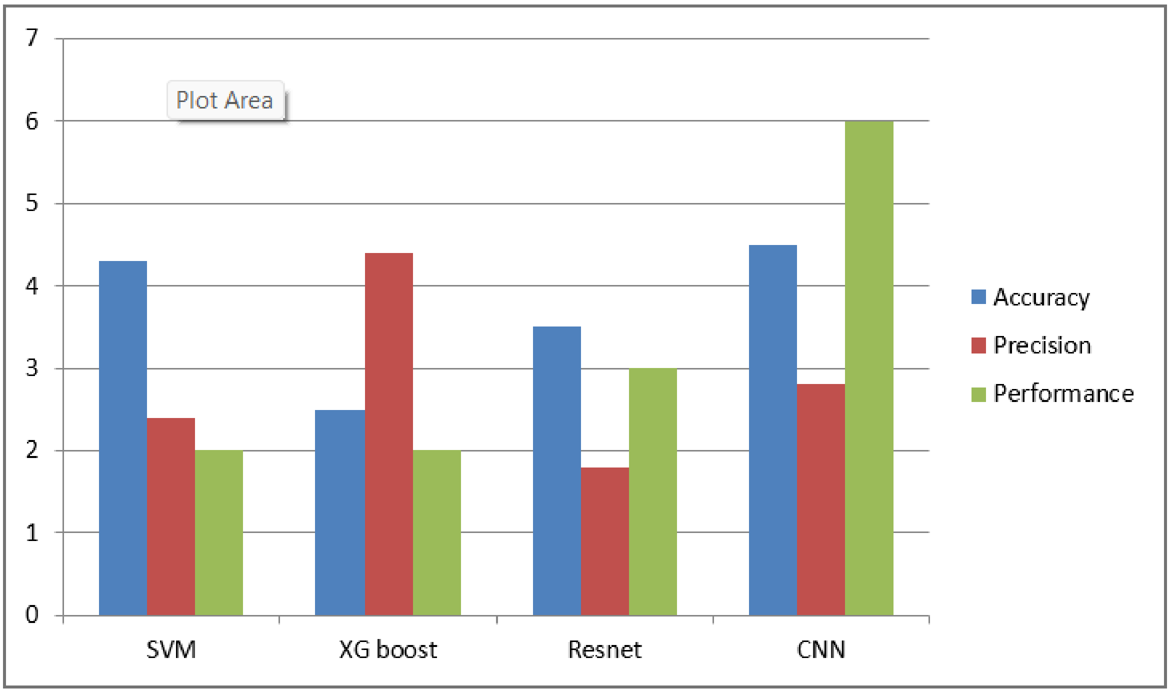
Global healthcare systems and medical practice can be enhanced by research in the critical topic of computer-aided early disease detection. Three clinically relevant discoveries, three essential anatomical landmarks, and two kinds of endoscopic polyp removal are identified in the gastrointestinal imaging dataset. Numerous illnesses affect the gastrointestinal tract; oesophageal and stomach cancers account for 1.8 million deaths and 2.8 million new cases per year. Endoscopy is considered the gold standard for gastrointestinal evaluation. A gastroscopy is used to inspect the upper gastrointestinal tract, which includes the stomach, oesophagus, and upper portion of the small intestine; a colonoscopy is used to examine the colon and rectum. These two tests are conducted as high-definition, real-time videos. Endoscopy equipment is costly and necessitates a high level of expertise. Preventing colorectal cancer requires early endoscopic lesion detection and removal, as well as the right kind of treatment. The ability of doctors to diagnose colorectal cancer varies, and if a doctor has limited ability to interpret the images, this could impact the diagnosis of colorectal cancer. The type of disease must be accurately diagnosed in order to begin treatment and conduct follow-up. Automatic diagnostics would therefore be greatly appreciated. The evaluation and identification of gastrointestinal malignancies may benefit from automatic diagnosis of pathological findings, which would increase the effectiveness and efficiency of medical resource usage.

## Convolutional Layers

Shape, texture, and color are only a few of the numerous variables found in the gastrointestinal dataset. Significant skill is needed for the manual feature extraction process, particularly when removing images from videos where the disease is not present in many of the photos and only occasionally appears in a few that the radiologist or other experts might overlook. CNN algorithms function by using convolutional layers to extract representative aspects of each disease. ResNet-50 has 49 convolutional layers, AlexNet has five convolutional layers, and GoogleNet includes several convolutional layers in addition to nine inception layers. In order to address the deep features and transfer them to the subsequent layer, these layers apply a series of filters and modify the weights throughout the training phase. In addition to decreasing the size of the feature maps, the average and max pooling layers also represent a group of pixels by using the average or maximum value between the groups of pixels. In order to supply the classification layers with information, the convolutional layers extract representative features from each image—a total of 9216 elements per image—and express them in feature maps.

## IV. RESULT AND DISCUSSION

In order to annotate the images in the validation data, rectangular boxes were created around each colorectal polyp. The output in the form of 0 and 1, which indicated the likelihood to which the region of interest belongs, was produced by the trained system after it had successfully shaped the region of interest with rectangular bounds. CNN computes the confidence it has obtained based on the probability. Greater confidence in adding the region of interest to a class of colorectal polyp will result from a higher likelihood score. The following scenarios are taken into consideration to verify the result. It was deemed accurate if there was greater overlap between the CNN and the actual location of the colorectal polyp than there was upon detectionWhen there was greater overlap between the CNN and the actual location of the colorectal polyp, the detection was deemed accurate. The box with a higher probability score is taken into consideration if two boxes were discovered on a single region of interest. Recent years have seen a lot of activity in the field of colorectal polyp detection and classification using deep learning techniques, likely due to the growing interest in employing artificial intelligence as a medical sector assisting tool. The reason for this research is that doctors occasionally overlook polyps because they are too tired or inexperienced to do the treatment. Unidentified polyps have the potential to worsen and eventually result in colorectal cancer (CRC), which is one of the main causes of cancer-related death. Although a number of approaches have recently been introduced, their effectiveness is hampered by a number of important problems, including blur, white light reflection, and insufficient training data. An overview of recently suggested techniques for colonoscopy-derived polyp detection is presented in this publication. Benchmark dataset analysis, evaluation metrics, frequent problems, standard building techniques for polyp detectors, and a review of recent literature work are all covered in the survey. As a precise examination of the gaps and patterns found in the evaluated literature, we conclude this paper with recommendations for further research.




Algorithm compparision

Understanding the significance of comparing various machine learning algorithms, such as svm, xgboost, and convolutional neural networks (cnns), specifically resnet, in terms of precision, performance, and accuracy, should be made easier by reading through your introduction and discussion section for polyp disease detection. examine the efficacy of three well-known machine learning algorithms: XGBoost, Convolutional Neural Networks (CNNs), and Support Vector Machine (SVM), focusing on the ResNet architecture for the identification of polyp diseases. These algorithms are selected because they are widely used in the interpretation of medical images and can manage intricate patterns of data. This study compares the performance, accuracy, and precision of CNNs based on SVM, XGBoost, and ResNet in the detection of polyp illnesses. Precision measures how well the algorithm avoids false positives by dividing the number of true positive predictions by the total number of positive predictions. Performance is measured using a variety of criteria, including as speed and computing efficiency. The accuracy of a model's predictions signifies their overall correctness.

## V. CONCLUSION

From extensive review, it was found that the existing models suffer from over fitting and gradient vanishing problems. To overcome these problems, a convolutional neural network- (CNN-) based deep learning model was proposed to efficiently detect and classify colorectal polyps from colonoscopy images. Initially, guided image filter and dynamic histogram equalization approaches were used to filter and enhance the colonoscopy images. Thereafter, Single Shot MultiBox Detector (SSD) was used to efficiently detect and classify colorectal polyps from colonoscopy images. Finally, fully connected layers with dropouts were used to classify the polyp classes. We have trained the proposed model on benchmark dataset and it has achieved better results with good computational speed even with small polyps which might get overlooked in colonoscopy. The trained proposed model achieved a good performance in detecting colorectal polyps which can help both patients and physicians from unnecessary treatments. For feature extraction, SSD was used for detecting and classifying colorectal polyps. Extensive experimental results revealed that the proposed model achieves significantly better results than the competitive models. The proposed model detected and classified colorectal polyps from the colonoscopy images with 92% accuracy. Colorectal polyp detection using deep learning is an exciting area of research, given the advancement in the healthcare sector and the increased interest in utilizing artificial intelligence to improve efficiency and reduce the workload of physicians. However, most existing methods do not perform well in real-life settings due to several common issues. Those issues include data disparity, white light reflection from colonoscopy, demand for high-end computational resources, and the different variations, sizes and shapes of polyps. This article reviews the latest trends and methods to automatically detect colorectal polyps from colonoscopy using deep learning techniques. Our review presents the benchmark colonoscopy datasets, evaluation metrics, common challenges, and various approaches to building colorectal polyp detectors. In addition, we analyze and discuss several recently proposed methods by looking into their implementation, reported performance and limitations. We conclude the study by discussing the trends, gaps and potential future directions based on the analyzed literature.

**REFERENCES**

[1] Haldar, Promit, Vanshali Sharma, Yuji Iwahori, M. K. Bhuyan, Aili Wang, Haibin Wu, and Kunio Kasugai. "XGBoosted Binary CNNs for Multi-Class Classification of Colorectal Polyp Size." IEEE Access 11 (2023): 128461-128472.

[2] Sasmal, Pradipta, Manas Kamal Bhuyan, Yuji Iwahori, and Kunio Kasugai. "Colonoscopic polyp classification using local shape and texture features." IEEE Access 9 (2021): 92629-92639.

[3] Nguyen, Ngoc-Quang, Duc My Vo, and Sang-Woong Lee. "Contour-aware polyp segmentation in colonoscopy images using detailed upsampling encoder-decoder networks." IEEE Access 8 (2020): 99495-99508.

[4] Liu, Ming, Jue Jiang, and Zenan Wang. "Colonic polyp detection in endoscopic videos with single shot detection based deep convolutional neural network." IEEE Access 7 (2019): 75058-75066.

[5] Kang, Jaeyong, and Jeonghwan Gwak. "Ensemble of instance segmentation models for polyp segmentation in colonoscopy images." IEEE Access 7 (2019): 26440-26447.

[6] Shin, Younghak, Hemin Ali Qadir, Lars Aabakken, Jacob Bergsland, and Ilangko Balasingham. "Automatic colon polyp detection using region based deep CNN and post learning approaches." IEEE Access 6 (2018): 40950-40962.

[7] R. L. Siegel, K. D. Miller, A. G. Sauer, S. A. Fedewa, L. F. Butterly, J. C. Anderson, A. Cercek, R. A. Smith, And A. Jemal, ‘‘Colorectal Cancer Statistics, 2020, Ca A, Cancer J. Clinicians, Vol. 70, No. 3, Pp. 145–164, 2020.

[8] H. Messmann, Atlas Of Colonoscopy: Techniques-Diagnosisinterventional Procedures. New York, Ny, Usa: Thieme, 2006.

[9] M. Arnold, M. S. Sierra, M. Laversanne, I. Soerjomataram, A. Jemal, And F. Bray, ‘‘Global Patterns And Trends In Colorectal Cancer Incidence And Mortality,’’ Gut, Vol. 66, No. 4, Pp. 683–691, Apr. 2017.

[10] L. Armi And S. Fekri-Ershad, ‘‘Texture Image Analysis And Texture Classification Methods—A Review,’’ 2019, Arxiv:1904.06554. [Online]. Available: Http://Arxiv.Org/Abs/1904.06554

[11] L. Armi And S. Fekri-Ershad, ‘‘Texture Image Classification Based On Improved Local Quinary Patterns,’’ Multimedia Tools Appl., Vol. 78, No. 14, Pp. 18995–19018, Jul. 2019.

[12] M. H. Bharati, J. J. Liu, And J. F. Macgregor, ‘‘Image Texture Analysis: Methods And Comparisons,’’ Chemometric Intell. Lab. Syst., Vol. 72, No. 1, Pp. 57–71, Jun. 2004.

[13] S. Fekri-Ershad, ‘‘Pap Smear Classification Using Combination Of Global Significant Value, Texture Statistical Features And Time Series Features,’’ Multimedia Tools Appl., Vol. 78, No. 22, Pp. 31121–31136, Nov. 2019.

[14] S. Ramamoorthy, R. Kirubakaran, And R. S. Subramanian, ‘‘Texture Feature Extraction Using Mgrlbp Method For Medical Image Classification,’’ In Artificial Intelligence And Evolutionary Algorithms In Engineering Systems. New Delhi, India: Springer, 2015, Pp. 747–753.

[15] E. Miranda, M. Aryuni, And E. Irwansyah, ‘‘A Survey Of Medical Image Classification Techniques,’’ In Proc. Int. Conf. Inf. Manage. Technol. (Icimtech), Nov. 2016, Pp. 56–61.