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WCE Images Polyp Segmentation System Using Convolutional Neural Network (CNN) With Stochastic Gradient Descent Optimizer

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***Abstract*—** Polyps in the small bowel have a chance of developing into cancerous tumors. As a result, it is important to recognize and treat such polyps at an initial stages. This would significantly boost the patient's chance of survival. Due to the rapid advancement of technology, wireless capsule endoscopy is regarded as a medical breakthrough. This allows for easy, painless, and inexpensive observation of the interior body, which is not visible to the naked eye. Simultaneously, the wireless capsule endoscopy's low-quality images are considered as its primary weakness. As a result, certain forms of polyps cannot be diagnosed from this wireless endoscopic imaging, even by a highly qualified physician. As a result, computer-aided polyp identification remains an ongoing challenge. This research introduces a novel segmentation algorithm for this purpose. The purpose of this research is to present a modified convolutional neural network (CNN) algorithm for wireless capsule endoscopy image segmentation that is based on dropout and the stochastic gradient descent optimizer. To increase feature extraction accuracy while decreasing time costs, this work analyses the CNN structure, the over fitting problem, and the combination of dropout and the SGD optimizer with the CNN. Additionally, this novel innovation was assessed using many polyp databases and its experimental results were compared to those of previously developed polyp segmentation techniques. The results demonstrate that our enhanced CNN outperformed state-of-the-art techniques.

***Keywords*—**Wreless capsule endoscopy, *CNN, Stochastic Gradient Descent Optimizer, Polyp detection, Image processing*

I. INTRODUCTION

The gastrointestinal tract is a critical component of the digestive system of a living thing [11]. It is situated in between large and small intestines. The small intestine is critical for digestion because it separates fluids, vitamins, nutrients, lipids, and carbohydrate. It is categorized into three sections: the duodenum, the jejunum, and the ileum. This is the ultimate stage of food absorption. Cancer in the gastrointestinal tract are extremely rare. The small intestine accounts for less than 5% of all cancer types. The majority of them arise in the colon, but the majority of cancer that enters the human's intestinal tract is extremely dangerous. Most disorders that occur inside the human stomach, such as tumours, ulcers, and bleeding, can be successfully treated and cured if detected early. Simultaneously, early detection of these diseases is extremely difficult. Numerous procedures, such as angiography, radiography, and ultrasonography, are used in the health sector to accomplish this. Nonetheless, these technologies were unable to produce any beneficial impacts.

Cancer has become into a serious medical condition in India over the last many decades. Additionally, its occurrence rate is increasing daily. Polyps must exert control over their beginning stage. Untreated polyps are likely to develop into malignant tumors. The Wireless Capsule Endoscopy (WCE) procedure has proven to be a benefit for the patient examination. Gabi Iddan and Paul Swain invented the WCE in 1997 [9][10]. WCE is a portable photographic instrument in the shape of a capsule. The capsule is 2.6 cm in length and 1.1 cm in width. It is a high-tech wireless camera equipped with cutting-edge technology. This WCE approach is used in a large number of medical centers, scientific research institutes, and oncology clinics throughout India.

In comparison to wired endoscopy, issues such as poor frame rate, limited operating time, and low imaging resolution remain unresolved problems in WCE. Even for an experienced physician, diagnosing anomalies in low-quality photographs is extremely difficult and time-consuming. As a result, the segmentation of wireless-capsule polyps remains a significant scientific challenge. Numerous research attempts have been made to successfully separate the polyp from WCE images for the last two decades. However, the dark background and the complicated structure of small intestine segmentation of polyp from WCE images remains an unresolved research problem. In this proposed research, the SGD optimization technique is combined with CNN to improve the polyp segmentation.

Section 2 of this article discusses the literature review. Section 3 details the suggested approach. The suggested polyp segmentation approach is validated in Section 4 using a real-time medical imaging data set. Finally, this method for detecting polyps in the GI tract has been summarized, and future study has been suggested.

II. Related Work

This section discusses in depth the previously proposed methodologies and algorithms for GI tract polyp segmentation.

Jaeyong Kang et al. created an Ensemble of Instance Segmentation Models for Colonoscopy Image Polyp Segmentation [1]. To improve performance, this technique combines two Mask R-CNN models with distinct backbone topologies (ResNet50 and ResNet101). Because many annotated colonoscopy images are not widely accessible, the Mask R-CNNs model was trained on the COCO dataset and then fine-tuned using the intestinal polyp dataset. To assess the proposed CNN architecture, we used three publicly available datasets on intestinal polyps: CVC-ClinicDB, ETIS-Larib, and CVC-ColonDB.
MING LIU et al. presented Colonic Polyp Detection in Endoscopic Videos Using a Deep Convolutional Neural Network Based on Single Shot Detection [2]. This technique evaluated the single shot detector (SSD) framework's ability to detect polyps in colonoscopy footage. SSD is a one-stage method that use a feed forward CNN to generate a collection of fixed-size bounding boxes for each item based on a collection of feature maps. Three distinct feature extractors were evaluated: ResNet50, VGG16, and InceptionV3. Additionally, multi-scale feature maps for ResNet50 and InceptionV3 were constructed using SSD. Additionally, they verified this method using datasets from the 2015 MICCAI polyp detection challenge and compared it to the method used by teams competing in the challenge, YOLOV3, and the two-stage method Faster-RCNN.

JAEYONG KANG et al. presented an ensemble technique for enhancing performance by combining two Mask R-CNN models with differing backbone topologies (ResNet50 and ResNet101) [3]. The model's mask R-CNNs were trained first on the COCO dataset and subsequently fine-tuned on the intestinal polyp dataset, as many annotated colonoscopy images are not readily available. To examine the proposed model, we used three publicly available datasets on intestinal polyps: CVC-ClinicDB, ETIS-Larib, and CVC-ColonDB.

Hemin Ali Qadir et al. published Improving Automatic Polyp Detection Using CNN by Taking Advantage of Temporal Dependence in Colonoscopy Video [4]. This method comprises of two stages: the proposal of a region of interest (RoI) by CNN-based object detector networks and the reduction of false positives (FP). By integrating the bidirectional temporal information collected by RoIs in a group of consecutive frames, the FP reduction unit exploits the temporal interdependence between image frames in video. This data is utilized to make the final determination.

III. Methodology

The suggested approach for polyp segmentation consists of two primary computer vision blocks: image pre-processing and the proposed CNN-based segmentation module. The proposed method's general architecture is depicted in Figure 1.

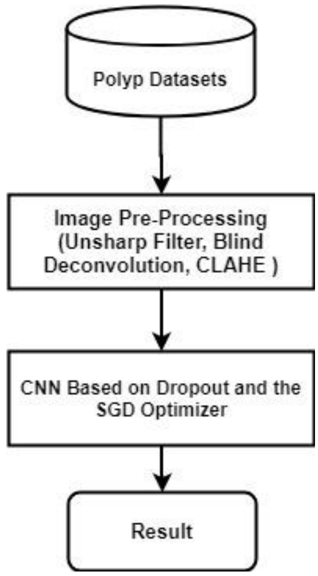

Figure 1 overall architecture of the suggested polyp segmentation algorithm.

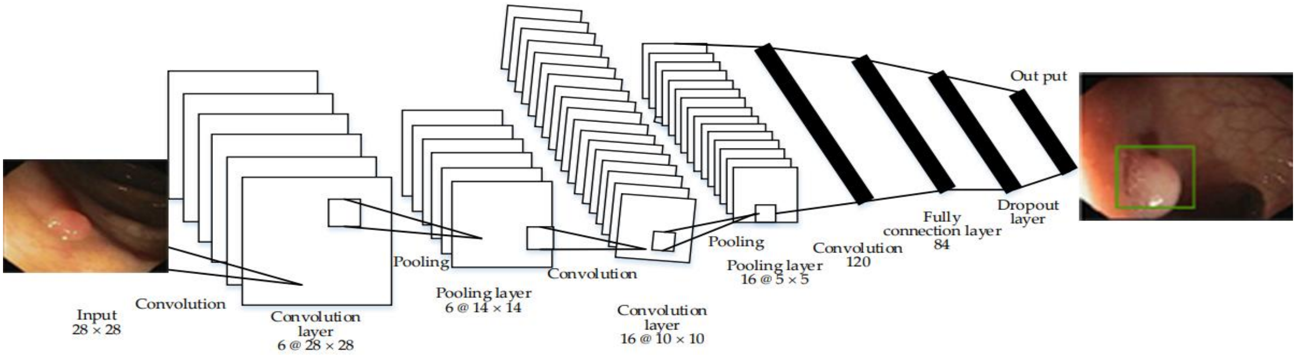

Figure 2 CNN model for polyp segmentation.

A. Image pre-processing

Segmentation of medical images needs proper pre-processing. Medical images are characterized by a high degree of noise, contrast, and volatility. To produce a more accurate segmentation result, these wireless endoscopic images must be combined with superior pre-processing techniques. In general, a wireless capsule endoscopy image has low contrast due to the low light conditions in which it is acquired. Unsharp filter, blind DE convolution, and contrast limiting adaptive histogram equalization methods were employed to pre-process the images in this proposed method. The unsharp mask filter is used to recover images that have been blurred. The images are restored using the blind DE convolution approach, and the contrast is balanced using CLAHE.

B. CNN architecture

As illustrated in Figure 2, this work creates a nine-layer CNN model that consists of an input layer, five hidden layers made of convolution and pool layers, a fully connected layer, and an output layer (softmax). A dropout layer follows the fully - connected layer in this configuration. In the training phase, the chance of the neuron node appearing in the test is p = 0.5, while in the trial phase, it is p = 1. Except for the output layer, all of the layers' activation functions are rectified linear unit (Leaky ReLU) functions. Conv2d performs two-dimensional convolution. Formula 1 is used to calculate the pooling operation (maximum pooling) (1).

$$x^i = f\left(\sum_j x_j^{(t-1)} * w_{i,j}^{(t)} + b_i^{(t)}\right) \tag{1}$$

where $w_{i,j}^{(t)}$ denotes the weight of the ith neuron in the jth class of the first convolutional layer; $b_i^{(t)}$ denotes the offset of the I class; * denotes the convolution operation of the proposed polyp segmentation system; $x_j^{(t-1)}$ r denotes the output of the j neurons in the first layer convolution; w denotes the output of the j neuron in the 1 layer, i.e., the input data for the l layer; and f () represents the activation function of the proposed polyp segmentation system.

C. Optimization

Stochastic gradient descent is a deep learning optimization approach that is frequently used to determine the hyper parameters that best fit the expected and actual outputs. It is an imprecise but effective strategy. It is often used in neural network training applications when combined with back propagation.

IV. Results and Discussion

A. System settings and software details

As part of our experiment, we used 1264 images randomly picked from 187 people with gastrointestinal tract polyps. This comprises 785 photos with polyps and 479 images without polyps. All of these images were taken at the Kims Hospital Trivandrum's scan Centre. Furthermore, 52% of these photographs were taken from male patients, with the most of them being between the ages of 50 and 60 years old at the time of the photograph. The photos are all 620 * 480 pixels in size. As indicated in Table I, this image data set was partitioned into four equal parts for training and testing. Therefore, 628 photographs of polyps and 384 images of non-polyps were taken for training, and 157 images of affected polyps and 95 images of non-polyps were taken for testing. Matlab 2016 and Windows 10 were utilized to conduct this experiment, and this programme was run on a machine equipped with an Intel i5 1-8 GHz processor and an NVIDIA GeForce GPU.

Table1 Database Image Details

Data Split	**Num. of Polyp Images**	**Num. of Non-Polyp Images**
Training	628	384
Testing	157	95

B. Evaluation Criteria

There are primarily two class labels in this suggested segmentation method, namely polyp and non-polyp. Four primary metrics were used to determine its accuracy. True positive, False positive, True Negative, and False-negative are the four types.

True positive: If the proposed methodology successfully identifies polyps, it is a true positive. It is abbreviated as TP.

True Negative: If the proposed framework accurately determines that there is no polyp, it is true negative. It is abbreviated as TN.

False Positive: A false negative occurs when the proposed framework wrongly depicts the presence of polyps. It is abbreviated as FP.

False Negative: A false positive occurs when the proposed framework falsely indicates the absence of a polyp. It is abbreviated as FN.

Accuracy, Precision, Recall, and F1-Score are all calculated using these four attributes. Accuracy is a key parameter for assessing the suggested CNN-based classification model. Typically, this is described by formula 2.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \tag{2}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

Precision is a term used to describe the accuracy with which correct diagnosis is made in classifications. Formula 4 is used to determine the precision.

$$PRE = \frac{TP}{TP+FP} \tag{4}$$

Recall is a term that refers to a classifier that properly classifies propositions as genuine positives. This is determined using formula 5.

$$REC = \frac{TP}{TP+FN} \tag{5}$$

The F1 score is used to determine the test accuracy of the classifier. Is determined by Precision and Recall. Formula 6 is used to compute it.

$$F1 = 2\ X\ \frac{Precision\ X\ Recall}{Precision+Recall} \tag{6}$$

The suggested algorithms' performance was assessed using state-of-the-art CNN approaches. We employ the FCN-AlexNet, FCN-GoogleNet, FCN-VGG, FCN-ResNet-50, FCN-ResNet-101, and FCN-ResNet-152 CNN algorithms. To provide a more accurate comparison, these state-of-the-art CNN algorithms are developed experimentally and their performance metrics compared to the proposed CNN algorithm. Tables 2 and 3 describe the experimental results for proposed and state-of-the-art approaches. Figures 7 and 8 exhibit a chart comparing the outcomes of proposed and state-of-the-art approaches.

V. CONCLUSION AND FUTURE SCOPE

There is a greater possibility that a polyp can develop into cancer at a later stage, that is why it is critical to detect polyps early. WCE is regarded as a major milestone in the medical industry. Simultaneously, doctors have difficulty detecting polyps at an early stage because to possible constraints of WCE imaging. The purpose of this study is to suggest a strategy for segmenting WCE polyps using CNN. While CNN is an excellent approach for image segmentation, its shortcomings can be overcome by adding a drop of layer between the convolutional and output layers and employing the GDS optimizer. As a result of this proposed strategy, it is simple to detect polyps during the initial stage. Additionally, this proposed technology has the potential to significantly reduce the amount of time doctors spend on polyp detection. Experiments with state-of-the-art CNN algorithms and the suggested CNN approach demonstrate that the proposed method produces extremely accurate results with a very quick processing time.

Table 2 Summary of Results for images with all Frames with Polyp

Networks	TP	FP	TN	FN	Spec	Prec	Rec	F1
FCN-AlexNet	263	18	1314	167	98.6	**93.5**	61.1	73.9
FCNGoogleNet	308	76	1301	123	94.4	80.0	71.4	75.5
FCN-VGG	362	41	-	125	-	88.1	71.0	78.6
FCN-ResNet-50	332	310	-	128	-	49.4	70.3	58.0
FCN-ResNet-101	280	38	1314	223	97.2	84.4	48.2	61.4
FCN-ResNet-152	279	28	1315	153	97.9	90.8	64.4	75.4
Proposed-CNN	387	39	1305	122	98.6	96.2	75.3	79.2

Table 3 Summary of Results for all Frames with Non- Polyp

Networks	TP	FP	TN	FN	Spec	Prec	Rec	F1
FCN-AlexNet	121	9	186	143	**95.3**	**93.0**	46	61
FCNGoogleNet	143	60	169	121	73.8	70	54	61
FCN-VGG	142	38	-	122	-	78	53	63
FCN-ResNet-50	137	310	-	127	-	30	51	38
FCN-ResNet-101	93	37	177	171	82.7	71	35	47
FCN-ResNet-152	119	21	183	145	89.4	84	54	53
Proposed-CNN	143	35	175	121	95.4	96	71	69

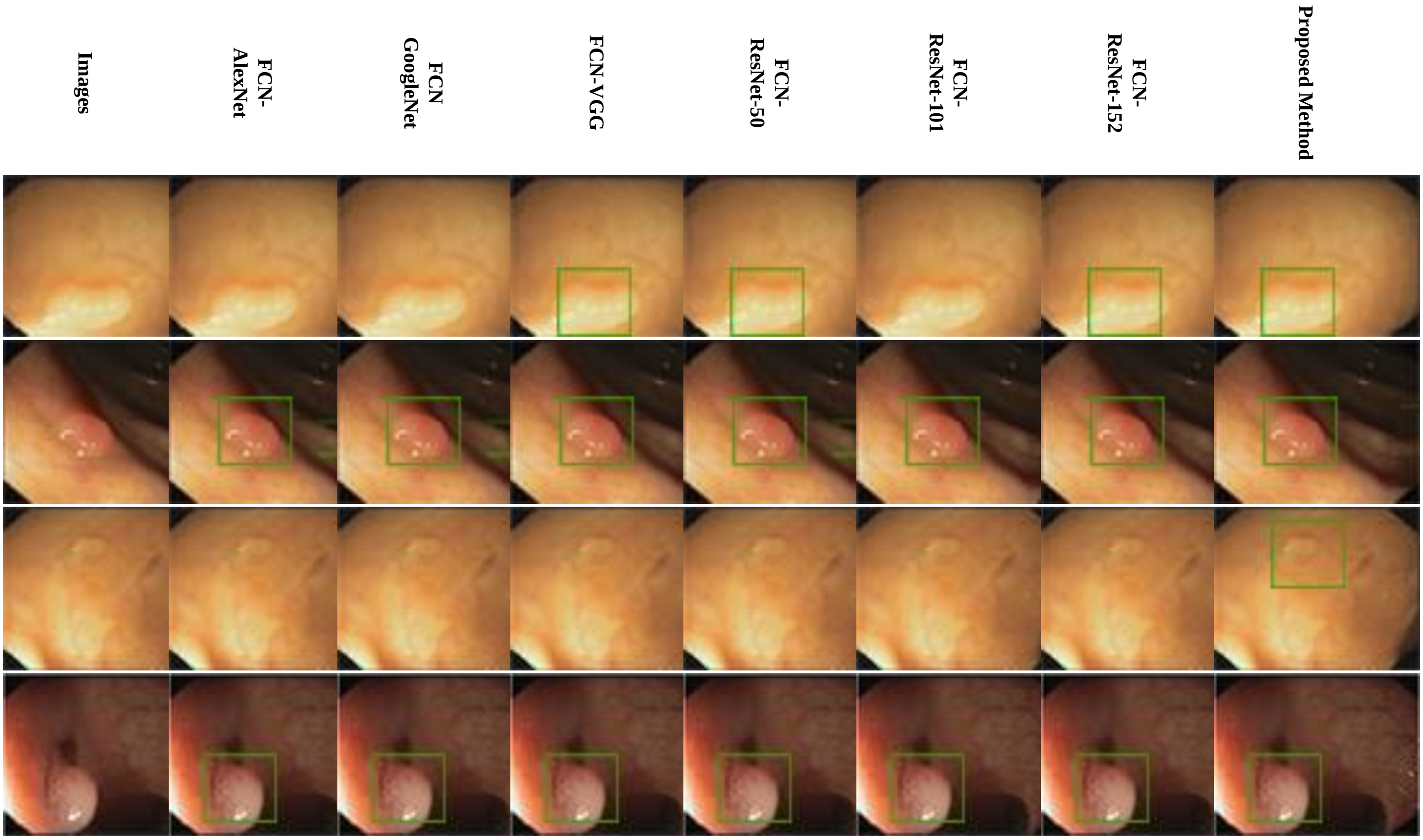

Figure 6 experimental results of proposed method and state of art algorithms.

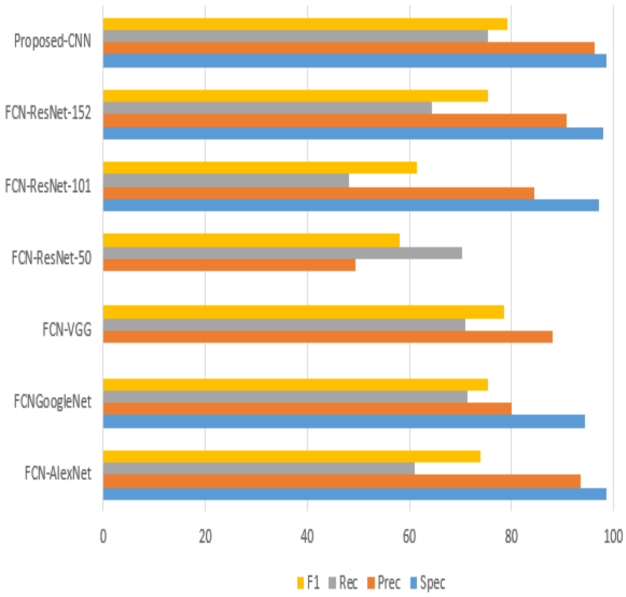

Figure 7 Results Comparison for images with all Frames with Polyp.

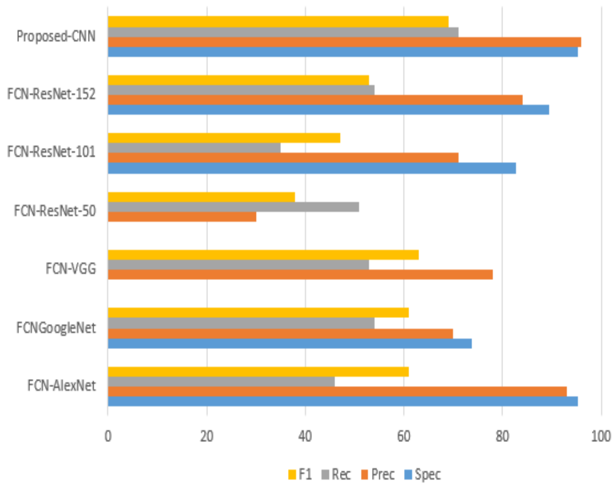

Figure 8 Results Comparison for all Frames with Non-Polyp

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