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Detection of Colorectal Cancer by Deep Learning: An Extensive Review

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ABSTRACT

Colorectal cancer, which is frequent, recognized tumours in both genders around the globe. As per the report generated by WHO in 2018, colon cancer placed in the third position, whereas 1.80 million individuals are affected. Precisely, it is the succeeding leading cancer, which is the second most common cause of cancer in females, and the third for males. The loss of control over the integrity of epidermal cells in bowel or malignancy can be the cause of colorectal cancer. An effective way to recognize colon cancer at an early stage and substantial treatment can reduce the ensuing death rates to a great extent. To perform Screening of Morphology of Malignant Tumor Cells in the colon, a Gastroenterologist may refer to cancer diagnosis tests for pathological images. In any Histology method, the process takes a significant duration of time due to infinite numbers of glands in the gastrointestinal system, which may lead to irreconcilable outcomes. By diagnosing through computer algorithms, can give practical and contributory results. Hence, accurate gland segmentation is one crucial prerequisite stage to get reliable and informative morphological image data. In recent times, the scholars applied deep learning algorithms to pathological image analysis for the diagnosis of cancer disease. We propose that features extracted from the diagnostic tests, given as input to a deep learning architecture used along with semantic segmentation algorithm, provide results that are accurate than the existing image segmentation algorithms. This work is the extensive review of deep learning architectures used for semantic segmentation on the histological images of the colon.

Key Words: Colorectal Cancer, Deep Learning, Gland Semantic Segmentation, SegNet, Histological Images

INTRODUCTION

The occurrence and fatality percentage of colorectal malignancy has much increased in contemporary years. More often, Pathologist's diagnosis depends on pathology reports of images and from biopsies, provides information about the escalation of cancer through the lymph and other organs of the body. This procedure not only takes a great deal of time and also price. However, it likewise has apparent constraints. The research study shows that the analysis of various pathologists has even more significant incongruity.[1] The primary factor for this incongruity is that the pathology medical diagnosis technique is subjective as well as easily affected by the atmosphere. Diagnosis of photos utilizing computer-based algorithms can be an efficient method for sustaining the medical diagnosis.[2]

As shown in Figure 1, the bowel is the collection of hollow organs took part in a long, twisting tube starting from duodenum to the anus. It absorbs the fluids and electrolytes,[3] and compels the solid waste to the rectum along with anus for purgation. The abnormal development of cells on the inward lining (mucosa) of the proximal colon or maybe distal colon, known as polyps, may be malignant or benign.

Many millions of organs in large intestine and rectum, take care of the absorbing of water as well as minerals and also secreting mucous for the regrowth of epithelial cells.[5]Nevertheless, an age far more than 50, a family history of colorectal cancers, Personal history of uterine, breast cancer, or maybe ovarian cancer can improve the possibility to affect by colorectal cancer. In sporadic cases exposure to carcinogen agents in the environment, specific genetic reasons may be the reasons. The stage of disease describes just how much it has spread, the grading stage of cancer helps to choose the best treatment.[6] Figure 2 demonstrates the stages with a number from zero to four.

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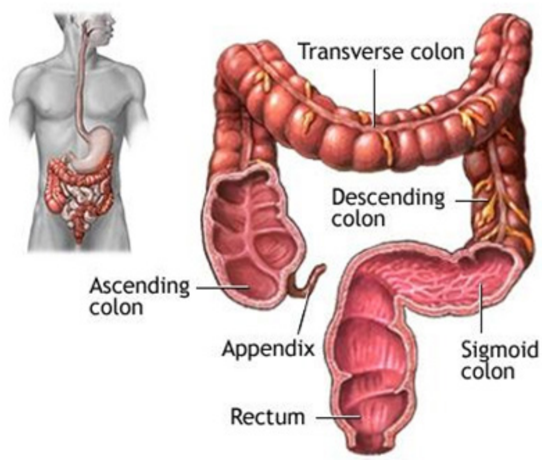

Figure 1: Anatomy of the large intestine[4].

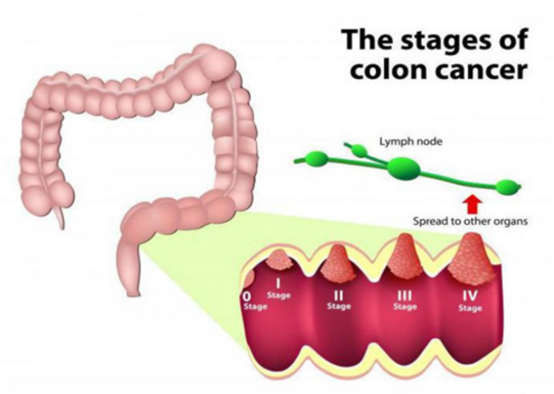

Figure 2: Stages of the colon or rectal cancer[7].

We can speculate the Colon Cancer by the symptoms like changes in feculence and its habits. A sensation of non-emptiness right after a feculence, blood traces in egesta which darkens the stool, bright-coloured red blood observed from the rectum, bloating, and some sort of discomfort in the abdomen. The heaviness in the stomach, which in turn results in refusing to eat for some time, unexplained weight loss. Unexplained iron deficiency in males, or maybe females after menopause. Perhaps nearly all of these signs might additionally signify other possible causes. It is advisable to consult a physician if these symptoms arise for more than four weeks. Stages in Colon Cancer are of four different stages,[8] and even further classification observed. Nevertheless, the main aim of colorectal cancer screening is to recognize irregular growths (polyps), before they developed into malignant. The medical society recommends a medical screening should connect different criteria and reduces the number of deaths.

Regular screenings

Individuals that had colorectal cancer before, who are more than fifty years of age, are observed with inheritance with a particular type of cancer, or perhaps with inflammatory sort of disease of the intestines, ought to take regular screenings.

Risk Factors

Factors which takes a person to a higher risk for developing colorectal cancer include various factors like[9]

Older age: Age plays a specific aspect in the predisposition to colon cancer. The statistics show that the age group near fifty is more prone to diagnosed. Sporadically could happen in young people. The average age of people who develop the disease is sixty-two years.

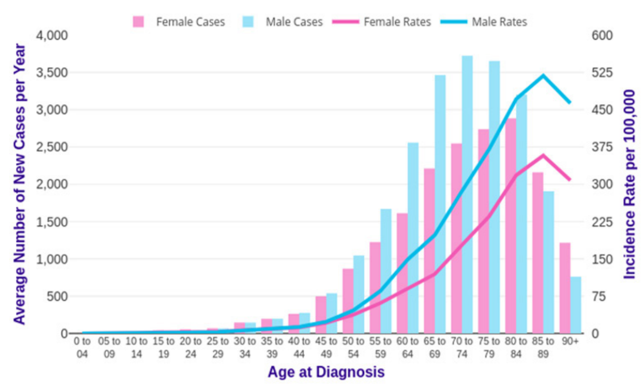

Figure 3: Age-specific incidence of colorectal cancer in females and males[10].

Figure 3 represents the intensity of colon cancer depend upon the ages, which particularly highlights that the older age people are affected with colon cancer.

African-American race: Greater possibility is found in African-Americans to get diagnosed with bowel cancer than the people of various other people of the world.

Malignant growth(Polyps): If malignant polyp resected in previous times, consequently there is a risk of colon cancer

Inflammation in entrails: Ulcerative colitis, chronic inflammatory disease, and causes of inflammatory disease of the intestines are creating many ways to chance of colon cancer.

Hierarchical Cause: The advancement of colon cancer escalated to a person when parents, siblings, or maybe kid infected with the same disease. If the diagnosis reports positive for more numbers, then the risk is very high.

High-fat, low-fibre diet: Low fibre diet and high in calories and fat (non-vegetarian with high in meats.

Indiscipline lifestyle: Inactive, dormant lifestyle is much more prone to colon cancer. Physical exercise is an excellent way to prevent and even may reduce colorectal cancer.

Pancreatic Diabetes: Diabetic issues and insulin consumption may have an increase in the risk of bowel or rectal cancer.

Obese individuals: Obesity causes an escalated peril of colorectal cancer and also increases the death rate with bowel cancer when compared to individuals who are with a healthy weight.

Smoking: Smokers are more prone to occur with colorectal cancer.

Alcohol: Frequent consumption of alcoholic beverages enhances the risk of Colon Cancer.

Radiology Medicine: Radiotherapy, which utilizes high doses of radiation to kill previous malignant cells and shrink tumours at the abdomen, raises the chance of rectal and colon cancer.

DIAGNOSIS

Screening can identify polyps before they start to be malignant, detection of cancer in the colon at the initial phases increases the chances of cure. The following are the preferable diagnostic procedures as well as screening methods for the detection of colorectal cancer.[11]

Test for occult blood in faeces

Sample of faeces collected from the patient. Furthermore, to test for occult blood to suspect colorectal cancer, but which takes a long process.

A DNA test on faeces

To test the presence of pre-cancerous polyps, discarded in the faeces, DNA mutations are examined and analyzed. Unlike an occult blood test, this gives results accurately, which distinguishes from cancer from polyps but fails to indicate a particular tumour is present.

Flexible Sigmoidoscopy

Screening is done through a sigmoidoscope, which is a thin tube with a light attached in the end to provide light inside the colon and rectum to observe a patient's colon. If some polyps recognized, then they are removed through colonoscopy after microscopic examination.

X-ray with Barium enema

The patient's trails are induced some amount of barium in the form of an enema, and X-ray is performed, which produces double contrast. Barium dye, used in the trails sticks to the inner lining of the bowel, producing more precise images of X-ray. Small polyps missed by the barium enema X-ray, recognized by flexible Sigmoidoscopy.

Colonoscopy

As represented in Figure 4, a colonoscope is similar to a sigmoidoscope rather have more length, and it is a slim tube with an electronic camera affixed at one end, to capture an inward view of the colon, and then displayed. During the test, if any polyp seems to be abnormal, biopsies, or tissue samples are taken. A colonoscopy is painless, but sometimes mild sedative is given to some patients not to feel pain while performing the colonoscopy. Before the colonoscopy, laxative fluid is given to the patients to clean the colon.

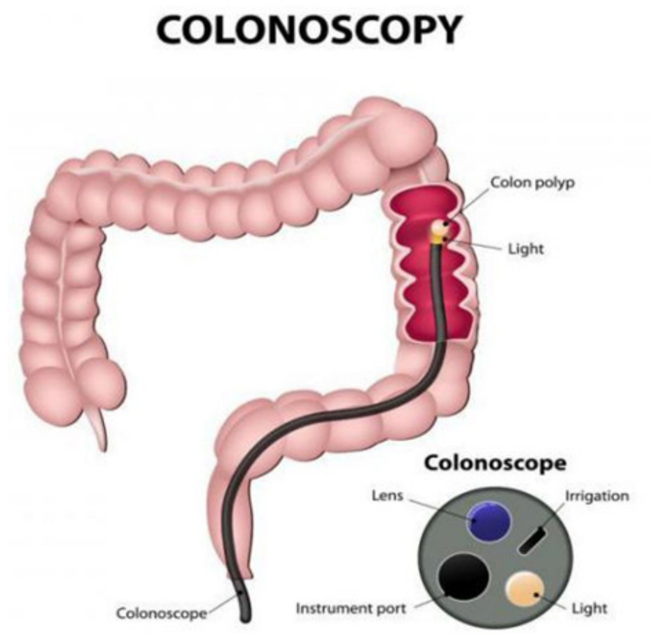

Figure 4: Colonoscopy.[12]

CT Colonography

Although colonoscopy is the best way for diagnosis of polyps and other abnormalities, in which some risks already analyzed. Perforation of inward tissues may result in bleeding and other complications. Hence, CT Colonoscopy is introduced. The patient put into the C.T. scanner and required observations made out using ultra-violet radiation passing through the body.

Scan and Imaging techniques

Ultrasound (Magnetic Resonance Imagining) scans can show the diffusion of cancer in the body. The waves can be penetrated inside the body and do not harm the internal tissues. Even though we may not get the best results, but some can deduce.

TREATMENT FOR COLON CANCER

The best treatment for colon cancer is finding and removal of polyps at an early stage by applying the screening. If the polyps are not cancerous, that means it does not consist of any nerves so that the patient will not feel pain during the removal process. If a polyp leads to cancer, it needs surgery or chemotherapy to kill the malignant tumour cells.

LITERATURE REVIEW

Recently in this field of computer vision, deep learning techniques, Deep Convolutional Neural Network (DCNNs) thoroughly used in object detection in images.[13,14] As shown in Figure 5, various objects can be detected very accurately using deep learning architectures compared with traditional feature-based object detection algorithms.

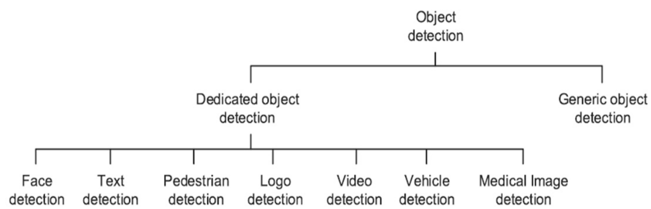

Figure 5: Dedicated and generic Object detection techniques.[13]

By the survey conducted by Saima Rathore et al., discussed several classification strategies, depending upon the spatial evaluation of colorectal biopsy images, and where they provide an in-depth summary of techniques in each classification. Where each classification includes spectral, gene, texture, serum, and O.O. Texture types of analysis.[15]Figure 6 describes the step by step procedure to detect colorectal.

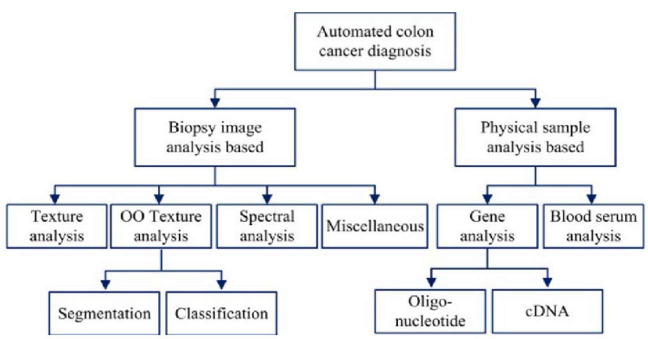

Figure 6: Classification of Colon Cancer Detection[15].

A unique DCAN given by Chen et al. deals with a multi-task learning framework,[16]yields accurate polyp detection, and segmentation in the colon. Multi-level contextual features are discovered depend upon an FCN, which can identify the contours of polyps in colon histopathological images very accurately. Aparna R et al. defined a novel algorithm to detect the polyps from colonoscopy images, by performing linear thresholding and Markovian Random Field to identify the saturated regions, segment the image depth-wise.[17] Then they used an SVM classifier to predict the condition of the disease by the help of colon correlogram vector and texture vector.

Among the various neural network models, CNN based semantic segmentation models,[18] FCN, is quite successful because of its accuracy results. One of the best models is VGG-16, which includes various techniques like bipolar interpolation used for upsampling the feature maps, to transfer the spatial level information, multiple skip connections are established. The conversion process of FCL to CNN is described in Figure 7.

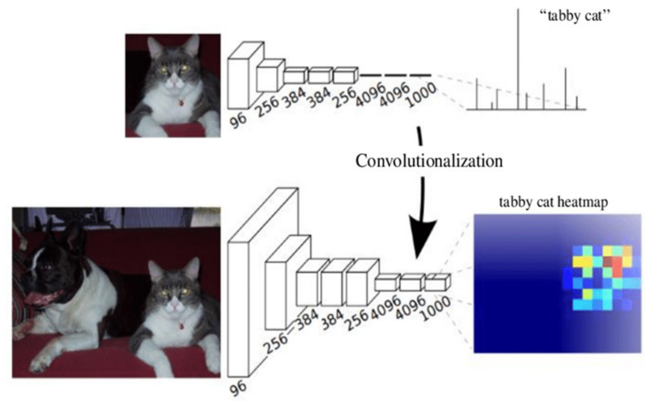

Figure 7: Converting-FCL of-CNN-to-convolutional-layers-20[18]

Chen LC et al. proposed a fully connected CRF attached to the final segment of DCNN,[19] which can overcome the poor localization property of deep networks. H.Noh et al. proposed a model named Deconvnet,[20] in which semantic segmentation performed by learning from a deconvolution network, in which the topmost layers(convolutional) considered from the VGG 16-layer network. The deconvolution network is composed of deconvolution as well as un pooling layers, used to perform semantic segmentation.

In the year 2012, AlexNet, a deep learning architecture proposed and which is one of the best architecture.[21] AlexNet is the champion of the ILSVRC.[21] The AlexNet, which contains a sequence of five convolution layers, and three fully connected dense layers associated with a softmax classifier used for image classification. In the year 2018, M Akbari et al. introduced a segmentation technique of polyps using CNN, in which a novel picture patch option technique performed in the training phase of the network. Moreover, in the period of testing, reliable post-processing on the chance map is done, which produced by the network.[22] U-Net has a diminishing pathway as well as an expanding pathway. During the shrinking pathway, the function data is raised, while spatial information lowered. The expansive path is a combination of the features and spatial information, which gives more accurate segmentation.

In the year 2017, Juan Jose Granados-Romero et al. proposed a review work on CCR, where they reported the factors increasing the CCR in humans and listed various types of tests to detect the malignant polyps.[23] In the year 2018, Ponzio et al. proposed an experimental research study on the classification of Colon Cancer, making use of Deep Convolutional Networks.[24] In this context, they work on an entirely new data set, which given for training to CNN models and then inspects the usage of transfer learning approaches.

Akshay et al. Proposed Automated polyp detection deep learning algorithm(CNN), from CT Colonography images for Colon Cancer Diagnosis.[25] In the year 2018, Urban et al. published a write-up about localization and identification of polyps with 96% precision. They consider the colonoscopy for the screening of the colon, and then the images are fed to a Deep network.[26]Lorena Guachi et al. discussed the concept of deep learning and hierarchical learning methods to segment the polyps in the colon with a Convolutional Neural Network.[27]

SIGNIFICANCE OF THE STUDY

The prime objective of my research is to develop an efficient Colorectal Cancer Detection Using Deep learning by Gland Semantic Segmentation from Morphology Images, which can detect the early stage Colon cancer.

SCOPE OF STUDY

To identify colon cancer following diagnosis are to be taken, CTC(Computed tomography colonography, Colonoscopy, Double-contrast BE, Sigmoidoscopy. In every test, the internal portions of the rectum visualized to the Rectal Surgeon, who can diagnosis the stage of rectal cancer. Image segmentation is a bit sophisticated task to map each pixel to its rightful class. It is applied to the MRI images to found the boundaries of glands and tissues in the colon to see the abnormal growth in the colon. Deep learning techniques, especially Convolution Neural Networks, are efficient for working with image analysis problems to get more accurate results.

EXISTING METHODOLOGY

Using CNN

Convolutional Neural Network used in image analysis in particular fields of medical and bio-informatics, for pattern recognition of glands or tissues.[28]CNN architecture organized as a sequence of steps comprising of iterating pooling and convolutional layers, which are fully connected.

The input information given through some defined size linear convolution filters moved among the pooling layers. To reduce the number of attributes, a non-linear down-sampling is used to reduce the spatial input size. Then ReLU is used in Deep Learning extensively, considered to be efficient than other functions because of the reasons it is not continuous and differentiable, and the problem of vanish for high activations not observed. Class label probability computed in the classifier layer, where the input information classified to a particular class based on the probability. And the last segment in the system generates the output image.

Using Fully Convolutional Network

The first FCN takes in-mapping from pixels to pixels, without disengaging the district proposition.[18] The limitation of CNNs to acknowledge and deliver marks just for explicitly estimated inputs originates from the completely associated fixed layers. As opposed to them, FCNs just have convolutional and pooling layers that enable them to make forecasts oneself-assertive estimated inputs.

Using U-Net

The system demonstrated as the contracting way, and a broad path,[29] The convolutional organize structures the contracting way. Each evolution in a Broadway contains an up-sampling of the element map followed by a 2x2 convolution layer that parts the number of highlight channels, a link with the correspondingly edited element map from the contracting way, and two 3x3 convolutions, each followed by a ReLU.

Using SegNet

SegNet is encoder-decoder network adhered by multi-class pixel-wise classification(softmax) layer.[30] The encoder network comprises of thirteen convolutional encoders, which are modeled particularly aimed to pattern recognition. The corresponding decoder layers are also 13 in number. In previous SegNet architecture, learning takes place in the down-sampling phase only. In the up-sampling phase, instead of the learning process, it uses a bilinear interpolation of weights. So, SegNet architecture cannot segment the contour information of the glands or polyps from the test images, taken from colonoscopy tests. So, we introduce a new architecture, which can segment the edges and boundaries of the polyps accurately.

Evaluation: The evaluation of images with ground truth images is done by various metrics, in particular, dice index and Hausdorff distance. Segmentation accurateness calculated by the dice index by using Eq(1),[31] which used to measure the similarity between GT object (G) pixels and SO(S) pixels.

$$Dice(G,S) = \frac{2*|G \cap S|}{|G|+|S|} \qquad \text{Eq(1)}$$

If the Dice index is 1, which indicates the exactly impeccable segmentation, but this finds the accuracy at pixel level only, so it is not accurate to calculate the segmentation at the gland level. So the object level Dice index is defined as in Eq(2),[31] as

$$Dice_{obj}(G,S) = \frac{1}{2}*\left[\sum_{i=1}^{n_G} \gamma_i * Dice\left(G_i, S_*(G_i)\right) + \sum_{j=1}^{n_S} \sigma_j * Dice\left(G_*(S_j), S_j\right)\right] \qquad \text{Eq(2)}$$

$$\gamma_i = |G_i| \Big/ \sum_{p=1}^{n_G} |G_p|, \sigma_j = |S_j| \Big/ \sum_{q=1}^{n_s} |S_q|$$

n_G Total number of no empty (G)GT glands, n_S Total number of SG (S) by the segmentation process, G_i describes the i^{th} ground truth object, G_j indicates the j^{th} Segmented Object. $S^*(G_i)$ denotes a GTO(G) that maximally overlaps G_i and $G^*(S_j)$ describes an object that overlaps S_j at maximum. Dice Score is the evaluation metric used to measure the similarity between two images. Contour based segmentation accuracy evaluated using object level Hausdorff distance between the shape of S and G.[31]

$$H(G,S) = \max\left\{\sup_{x\in G}\inf_{y\in S} d(x,y), \sup_{y\in s}\inf_{x\in G} d(x,y)\right\} \quad \text{Eq(3)}$$

In Eq(3), Euclidean distance denoted by d(x, y) between the pixels x of G and y of S. If the obtained Hausdorff distance is small, indicates the higher similarity between the contours of S and G. if S Equals to G, which indicates the H(G, S) is zero.

$$H_{obj}(G,S) = \frac{1}{2} * \left[\sum_{i=1}^{n_G} \gamma_i * H(G_i, S_*(G_i)) + \sum_{j=1}^{n_S} \sigma_j * H(G_*(S_j), S_j)\right] \quad \text{Eq(4)}$$

Object wise Hausdorff distance is implemented as Eq (4) to find the distance between object wise boundary-based segmentation accuracy.

RESULTS AND ANALYSIS

A polyp that causes cancer in the colon is challenging to detect because the colon consists of millions of Glands. Colonoscopy reduces the risk of colorectal cancer by detecting and removal of polyps. By feeding these images as input to the deep learning architectures which use a combination of semantic segmentation to bring better results with a limited number of samples.

Table 1: Comparison between various architectures in image segmentation.

S. No.	Architecture	Dataset	Number of images	Total no.of Metrics	Accuracy
1	CNN	CVC-ColonDB database	300	6	74.80% (Sensitivity)
2	SegNet	Warwick-QU	85	2	0.8636 (Dice Score)
3	U-Net	PhC-U373	35	3	92% (Intersection over union)
4	FCN	PASCAL VOC 2011	736	4	62.7 (Mean I.U.)

The above table shows the different architecture and its results in terms of accuracy delivered to their evaluation metrics. The U-Net architecture has more accuracy of 92% of evaluation metric Intersection over the union on the dataset PhC-U373.[29]

Table 2: Comparison between various architectures in object detection

Method	Backbone	Input Size	*Frames Per Second* (FPS)	Mean Average Precision(mAP) %		
				Visual Object Classes (VOC) 2007	Visual Object Classes (VOC) 2012	Common Objects in Context (COCO)
R-CNN	AlexNet	227*227	<0.1	58.5	53.3	-
SPPnet	ZF-5	~1000*600	<1	59.2	-	-
Fast R-CNN	VGG-16	~1000*600	0.5	70	68.4	19.7
Faster R-CNN	VGG-16(ResNet-101)	~1000*600	7	78.8	70.4	21.9
YOLO	GoogleNet	448*448	45	63.4	57.9	-
YOLOv2	Darkent-19	544*544	67	76.8	73.4	21.6
YOLOv3	Darkent-53	320*320	45	-	-	28.2

The above table describes the results generated by various architectures by considering the measures mAP, FCS, and trained and tested on various Deep learning architectures.

CONCLUSION

In the current article, an attempt had been made to present various research findings which were made by several authors and researchers to identify the Colorectal Cancer. From the previous works, it is understood that it is always better to identify the disease in an earlier stage to get maximum chances of recovery from cancer. After a detailed study on these traditional methods for identifying the Colorectal Cancer, the accuracy of identification and the time to identify the disease is more. From the previous works, it is also observed that by using the deep learning mechanisms, the results are little encouraging. The results obtained by traditional feature-based analysis procedures had already discussed in the current article. From the results obtained earlier, we understood that the utilization of deep learning techniques with the combination of semantic segmentation method will be the best choice for getting good results in terms of identifying the disease. We also try to plan for implementing the hybrid deep learning models for better identification of disease in the earlier stages as our future work.

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