International Journal of Advanced Research in Engineering Technology & Science

ISSN: 2349-2819

Email: editor@ijarets.org Volume-9, Issue-7 July – 2022 www.ijarets.org

A Review on the Diagnosis of Colon Cancer Stages Using Deep Learning Techniques

Pooja V
Department of Computer Science
University of Kerala.
Kerala, India
poojasreeram2515@gmail.com

Chempak Kumar A
Department of Computer Science
University of Kerala.
Kerala, India
chempakkumar1979@gmail.com

D.Muhammad Noorul Mubarak
Department of Computer Science
University of Kerala.
Kerala, Indiaa
dmnmubarak@gmail.com

Abstract—

Colon cancer is the second most common cancer in females and third most cancer in male. It is a malignant tumor arising on the walls of the large intestine or rectum. Common symptoms are rectal bleeding or blood in the stool, dark-colored stool, and change in bowel habits, change in stool consistency, constipation, diarrhea, narrow stools. Tumors fall into two categories: there are benign (noncancerous) tumors and malignant (cancerous) tumors. In this review we consider 20 differently published papers regarding the segmentation, classification and detection of colorectal cancer using the deep learning models and compared the results. We also discuss the various limitations and the challenges in the diagnosis of Colon Cancer.

Keywords—Colon Cancer, Convolution Neural Networks, Deep Learning, Colorectal Cancer, Polyp

I. INTRODUCTION

The uncontrolled growth of cells in a human body may be termed as cancerous cells. The abnormal growth of cells in the colon or rectum then it is called colon cancer or rectum cancer that is colorectal cancer. In the inner lining of the colon when the cells are growing then it is called polyp. All the polyps are not cancerous in nature it is known by which type of polyp is present in it. There are 3 types of polyps they are (1)) Hyperplastic polyps and inflammatory polyps. This is seen in general so it is not precancerous polyp. (2) Sessile serrated polyps (SSP) and traditional serrated adenomas (TSA) this is also treated as adenomas it has a high risk for cancer. (3) Adenomatous polyps (adenomas) this is a precancerous condition that may be changed to cancer. The 3 types of adenomas are tubular, villous, and tubulovillous. Colorectal cancer is also known as Bowel cancer. An early prognosis of polyps and the removal of lumps from the colon surface are most important for prevention of CRC. Colonoscopy is the golden standard for screening CRC

.

Polyp can be detected and classified by using various Deep learning algorithms. Deep learning is based on artificial neural networks, where the gaining of knowledge imitates the human learning approach. Some supervised learning models are Classic Neural Networks (Multilayer Perceptron's, MLP), Convolutional Neural

Networks (CNNs), and Recurrent Neural Networks (RNNs). The MLP is a feed forward neural network that has an input layer, hidden layer and output layer. CNN is a more efficient DL network for classification. It has a convolution layer, max pooling, flattening, and full connection. In CNN the convolution layer extracts the feature maps, which is then applied on to a set of pooling filters for removing the redundant features. The most relevant features are arranged into an array structure through the process of flattening using the FC layer.RNN is used for predicting sequences.

For object detection, The YOLO (You Only Look Once) [1] and FRCNN [2]are the best models as compared to others. In this we give an input image and give the result as bounding boxes. In image segmentation, we give an input image and get the output as a mask image. The best image segmentation models are Mask RCNN [3], UNet,[4] and Segnet[5]. Image detection is the task of locating an object in an image. CVC-Clinic, CVC-Colon, Etis-Larib, Kvasir, CVC-ColonDB, CVC-ClinicDB2015 are various databases having endoscopic videos and images that are commonly used for all networks.

II. REVIEWED WORKS

Xi Mo et al. [6] presented a faster region-based convolutional neural network (Faster RCNN) for an efficient approach for Polyp Detection from Endoscopic Videos. The Dataset used are CVC-Clinic2015 (CVC15), which contains 612 still frames, selected from 29 endoscopic videos, CVC-Clinic2017 (new database) has up to 18733 frames, CVC-ColonDB (Small public dataset), CVC-EndoSceneStill. The CVC group combines CVC-ColonDB with CVC-ClinicDB2015. In FRCNN [2], there is a backbone structure called VGG16 that has benefits for its deep feature extraction process besides its relatively high speed. For dataset – CVC15train we get Precision as 86.2%, Recall as 98.1%, F1-score as 91.7%, and F2-score as 95.6%. The proposed method exhibits potentials for reaching the best performance on precision, as well as yields competitive results in other metrics.

Ashkan Tashk et al [7] employed an innovative Convolutional Neural Network (CNN) approach for automatic segmentation of colorectal polyps. In the pre-processing stage, the input colonoscopy images are transferred to three color spaces. Then these colored images are given to UNet architecture [4]. CNN has a U-Net layer graph. The benefits of U-Net as compared with others are it is fast and it is compatible with various input dimensionality. Some morphological operations are applied to the post-processing approach for removing redundant pixels for accurate results. The result of the proposed method with post-processing is accuracy as 99.6%, Precision as 70.2%, and Recall as 90.9%, and F1-Score as 79.23%. The proposed method without post processing, result in an accuracy of 99.1%, Precision as 92.82%, Recall as 77.67%, and F1-Score as 84.57%.

Sebastian Grossa et al [8] explored an automated inter-and intra-observer independent system for the automated classification of colon polyps in endoscopic image data into three different kinds of polyps such as hyperplasia's, adenomas, and Inflammatory based on vessel structures for the better classification performance. At first, specular reflections are removed from the images, and also the image is converted in HSV color space. Then windowed background equalization is applied to the grey-scale image and find Region of Interest (ROI). This output is done with phase symmetry filtering to find dark structures on brighter backgrounds. The result of phase symmetry filtering is exploited in two ways. Firstly, thresholding and a non-maximal suppression algorithm are applied secondly; it is used as a cost matrix. Apply hysteresis thresholding and Vessel segmentation to the phase symmetry filter for noise removal. For feature selection, an algorithm is developed with Sequential Forward Feature Selection (SFFS) and Sequential Backward Feature Elimination (SBFE). Another algorithm is inspired by probabilistic meta-heuristic Simulated Annealing (SA). During each iteration the algorithm determines randomly whether a feature is added to, replaced in, or removed from the current feature set. The best result was achieved by SA using only eight features (96.2% accuracy). The segmentation algorithm proposed in this paper improved the polyp classification accuracy from76.6% (PS+FM) to 85.7% (PS+HT). Simulated Annealing led to the best results with an accuracy of 96.2% (sensitivity: 97.6%, specificity: 94.2%, PS+HT+SA) using a combination of eight features.

Isabel N. et al [9] carried out automatic detection of colonic polyps in wireless-capsule endoscopic images. This is an analysis of geometric features and image intensity features also that some variational segmentation processes are applied on images. At first, use Gaussian and mean curvatures to check it is suitable for detecting colonoscopic images from the wireless capsule. Then Chanand Vese's segmentation model is used and there are some numerical explanations also. Using Gaussian and Mean Curvatures, we can easily compute the geometrical characterization of polyps so we can easily identify polyps from the capsule images. The main approach proposed, which relies on the segmentation of the curvature-based function P, does not do the complete segmentation; it only detects the higher part of the polyp. However, we believe that the detection of the polyp is, by itself, a good result, and this is a fully automatic process.

Yao Yao [10] et al. is implementing Automated Classification and Segmentation in Colorectal Images Based on Self-Paced Transfer Network. It is very difficult to find endoscopists to classify colonoscopy images as normal tissue, polyp, and tumor. In Preprocessing, the collected images are split for training, validation also for testing set. Then that image is resized to maintain integrity. In this method, a network pre-trained image net is used for training for better classification performance. This VGG19[11] model is transferred to the STVGG Model; here a self-paced learning algorithm is used for better classification of unbalanced sample images. Next for segmentation, the Unet network framework is used for endoscopy images. Then compare with other methods and finally the STVGG model gets the more accurate result for classifying the polyps as normal one and tumors. This results in high classification accuracy i.e. 96% and good segmentation results as compared with other methods such as TLVGG but this works better using Unet[4] and Segnet[5].

K. Gayathri Devi et al [12] introduced an Automatic Segmentation of Colon in 3D CT Images and Removal of Opacified Fluid Using Cascade Feed Forward Neural Network. This is starting with the identification of air-filled regions so that the foreground should be separated from the background to remove air. These regions have small intestines, lungs, and bowels, mixed (colon, small intestine), noise, etc so it could be differentiated by positive class and negative class. The positive class contains mixed and colon. In the proposed algorithm the air packets are removed by using the Otsu thresholding method then it gives the approximate location of the colon. .Thus the maximum number of connected regions that are to be considered for the segmentation of lungs is done by an algorithm that works based on Moore-Neighbor tracing algorithm modified by Jacob’s stopping criteria. Then this is followed by some morphological operation i.e. image erosion followed by dilation. Extraction of fluid-filled is implemented by using a cascade feed-forward neural network. So the region of colon segmented by the proposed algorithm is compared with manually segmented colon using ITK snap software. So the performance is evaluated by accuracy, dice coefficient, sensitivity, etc. This segmentation algorithm is used to identify the polyp attached to the walls of the colon. The segmented portions are highlighted in red color and the bowels that are to be removed are highlighted in green color. This segmentation method attains 98% of accuracy, whereas the Graph Cut Approach is 90.8% and Level Sets is 97.6%, specificity value is 97%.

Sae Hwang et al [13] proposed an Automatic Polyp Region Segmentation for Colonoscopy Images using Watershed Algorithm and Ellipse Segmentation. In this there are three steps to follow for polyp segmentation. They are Gradient Magnitude Construction, Initial Segmentation, and Ellipse Segmentation. Many endoscopic videos have low-contrast video frames. To achieve gradient information, a match filter method is used to detect clear boundaries. After that, it uses a median filter for noise removal. Match filter needs to have a set of filters to get a set of filters; the second derivative of Gaussian is used. For initial segmentation, based on different intensity values polyp is recognized as region uniformity but we want edge uniformity. So we use the marker-controlled watershed algorithm for contour detection. Object boundaries are determined by watershed lines. In each segmented region, it determines ellipses by the ellipse fitting method. Then using the thresholding method binary edge map is created to detect ellipses. The proposed polyp segmentation technique 93% of sensitivity and 98% of specificity.

Debesh et al [14] suggest Kvasir-SEG: A Segmented Polyp Dataset. The original Kvasir dataset consists of 1000 images while 13 images are removed from the polyp dataset for better quality. This data set is limited to frame classification and it contains polyp images and their corresponding masks. It contains 3 folders: polyp images, mask images, and JSON folder which contains a bounding box of corresponding images. It can be downloaded from https://datasets.simula.no/kvasir-seg/. Kvasir dataset is used for segmentation, localization, and classification of polyps. In this efficient FCM (unsupervised clustering algorithm) and deep-learning ResUNet architecture is implemented. For the implementation of FCM, first do some preprocessing technique for noise removal and apply threshold value than doing dilation from that reshaped the image and give input to FCM as 1D. ResUNet model, we used image augmentation techniques like flipping, random crop, scaling, rotation, brightness, etc on the training dataset. We used five convolutional blocks both in the encoder and the decoder of the ResUNet model. The FCM attains a Dicecoefficient of 23% and a mean IoU of 31%. The ResUNet model attains a Dice coefficient of 78% and a mean IoU of 77%.

Hemin Ali et al. [15] popped up the question Does a Deeper Feature Extractor CNN Always Perform Better? For Polyp Detection and Segmentation using Mask R-CNN. For implementing this we use 2 datasets: 1) CVCClinicDB containing 32 different, and 2) ETIS-Larib containing 36 different polyp images. In this evaluation of mask, RCNN is compared with CNN feature extractors so it is a task for finding the best feature extractors. We select three feature extractors: deep CNN (e.g.,Resnet50[16]), deeper CNN (e.g., Resnet101), and complex CNN (e.g., Inception Resnet[17] (v2)). From this, we choose one to extract features for predicting region proposals by RPN. Then proposed an ensemble model for combining the twoMask R-CNN models with two different CNN feature extractors. In training to prevent the overfitting of the dataset, it uses different augmentation strategies. Inception Resnet and Resnet 101 give the best for object classification. Mask R-CNN with Resnet50 gives recall of 83.49%, precision of 92.95%, dice 71.6%, and Jaccard of 63.9%. In ensemble results, the ETIS-Larib dataset is used for validation. Here, use a threshold value for the auxiliary model and do some preprocessing to decrease FP detection. Resnet 101 Could improve recall by 2.93%, dice by 4.12%, and Jaccard by 4.38 whereas Resnet Inception could only improve recall by 0.46%, dice by 3.13%, and Jaccardby 3.51%. Precision got decreased in both cases. The improvement in detection is less than in segmentation; they both are precisely segmented by Resnet101 and Resnet Inception with a confidence of 99%. Our Mask R-CNN with Resnet 101 Achieved the highest precision (80%) and a good recall (72.59%).

Debesh Jha et al. [18] suggest Real-Time Polyp Detection, Localisation, and Segmentation in Colonoscopy Using Deep Learning. For automatic polyp detection, segmentation, and location using SOTA methods, here the Kvasir SEG data set is used and in previous studies, it especially focused on polyp color and texture and crafted descriptors - based feature learning. We used 880 images for training and the remaining 120 images for the validation process. The choice of methods for detection and segmentation (e.g., UNet [4], Faster R-CNN[2]), speed (e.g., UNet withResNet34[19], YOLOv3[1]), and accuracy (e.g., PSPNet, FCN8, or DoubleUNet) or a combination of all (e.g., DeepLabv3+[20], YOLOv4). YOLOv4 is 3× faster than RetinaNet and is good for average precision and IoU. The validation on the image net model the accuracy of ResNet101 is slightly better than ResNet501.YOLOv4 with Darknet53 and CSP backbone is the best approach for polyp detection and localization tasks. For semantic segmentation tasks, UNet with a ResNet34 backbone showed is better compared to other methods. The method obtained the highest FPS of 35. The most competitive method to UNet with ResNet34 backbone was DeepLabv3+, which is having an accurate feature map for object segmentation tasks. UNet with ResNet34 and DeepLabv3+ backbone provides the best trade-off speed and accuracy over several SOTA methods. Small polyps are handled by the use of spatial pyramid layers.

Aparna Ratheesh et al [21] has put forward an Efficient Method for Polyp Detection and Density Estimation Using MRF Segmentation in Colon Endoscopy. In preprocessing stages, the images from the endoscopic videos are circular so linear exploration is done on images. Then it is converted into HSV color space and for histogram image equalization. Then thresholding is applied to find the region of interest and Markovian Random Field is used for segmentation. For implementing the MRF algorithm, texture analysis is done by blades algorithm, and using thresholding technique texture content is estimated. SVM is used for the classification of cancerous polyp. The accuracy of the proposed method is 96.7%.

Patrick Brandao1 et al [22] is proposed Fully Convolutional Neural Networks for Polyp Segmentation in Colonoscopy. MICCAI 2015 data set is used for polyp detection and segmentation. There are 3 convolutional architectures (AlexNet[23], GoogleNet[24], and VGG[11]) in FCN[25].There is a comparison between these. At this, there is no segmentation is done; this is evaluated by using common segmentation evaluation metrics such as mean pixel precision and mean pixel recall. In segmentation, FCN-VGG produces accurate segmentation. While in detection, FCN-VGG has a deeper and high dimensionality architecture that allows complex colon scenes to encode than FCN-AlexNet. Finally, in computational speed, FCN-VGG is 5 times slower than other architectures.

Finally, FCN-VGG has better overall results for polyp detection and it has precision and recall as 73.61% and 86.31% respectively.

Sean R. Stanek et al [26] presented Automatic real-time capture and segmentation of endoscopy video. Capturing endoscopic videos on a Windows workstation with capturing hardware is endo capture. This endo capture works from 6 Am to 5 30Pm except for weekends. It takes inside and outside images every 10 seconds. To filter these images, it has 3 components: video capture, image analysis, and video encoding. In which video capture, with the help of hardware components it takes a series of 720 x 480 x 24 bits-per-pixel images from the video and audio data. For processing these data with a grabber filter and eventually, it is stored on the FIFO buffer. Then the decision-making part of the system is the image analysis part whether the image is inside the useful image or outside image of the colon. It is done by using an algorithm. Then frames from the video buffer are completed then there is no next frame from the buffer is done by the video encoding part. And also there is a synchronization and priority part in which data flow is managed by the synchronization part and some components want more response time than others then priority is given to each thread for processing else the operating system will reject the process. The endocapture system attains segment-based sensitivity of 100% and specificity of 99% out of 173 videos.

Tsubasa Hirakawa et al [27] implemented SVM-MRF segmentation of colorectal NBI endoscopic images. In this, a computer-aided system is to be developed to evaluate the condition of the tumor. Here the NBI images of colorectal tumors are classified into 3 types: they are type A, B, and C3. There is a previous work known as “computer-aided colorectal tumors classification in NBI endoscopy using local features” by Tamaki et al [28] trying to find which part of NBI image falls on to which type of class of endoscopic images. This is done by using Bag of visual word framework with densely sampled SIFT descriptors such as DoG SIFT, Grid SIFT,Diff SIFT (descriptor used in this for Type c3), and histogram based on visual words used for segmentation, and a linear kernel of SVM classifier is for classifying the images. The output of this system is not a label but is the posterior probability of type classes. Three colored temporal curves are used to represent the posterior probability. As the continuation of this work, it has used SVM classifiers with a Markov Random Field (MRF) minimization framework. At first, the NBI images are divided into small patches then classify each patch by using SVM classifiers. One type to another is varied with some features: they are not clear borderline, no location before endoscopy images; the visual appearance of the texture is changed. Then NBIimages are used for training the SVM classifier of each type then an MRF grid of spacing 10 pixels is constructed for each NBI image. The pchange in performance of the segmentation results as the probability p takes values of 0,0.05... 0.95, 0.99. So the system automatically segments True labels of images are in Type A and part of highlighted images are in Type B.

Jaeyong Kang et al [29] present an Ensemble of Instance Segmentation Models for Polyp Segmentation in Colonoscopy Images. This ensemble means that two mask RCNN[30] models with different backbone structures. There are 3 components of first data augmentation. In which Vertical flipping, horizontal flipping, random rotation, random scaling, random shearing, random Gaussian blurring, random contrast normalization, random brightness ranging, and random cropping and padding these operations are performed. Second Mask RCNN[3] with Transfer learning, which is an extension of FRCNN[2] it has 2 backbone structures they are Resnet50 and Resnet 101. The Mask RCNN has a 2 stage framework; the Region proposal network (RPN) integrates the content in one network to improve the detection speed. The second stage has two parallel branches. Bounding box branch for detection and mask branch for segmentation. In the ensemble method, the bitwise operation is done with 2 backbone structures. Three data sets are used -CVC-ClinicDB for training and ETIS-Laraib and CVC-ColonDB for testing. The proposed method has 77.92% precision, 76.25% Recall, and 69.46% interception over the union.

Ashkan Tashk et al [31] proposed Fully Automatic Polyp Detection based on an U-Net[4] architecture and Morphological Post-process. This works in three sections. First preprocessing, in this colonoscopy frames are converted into CMYK, La*b* and gray-level. Then Unet architecture. CNN has an Unet architecture independent of input image size, a size patching solution is employed. Unet has two stages. The first stage is to feature extraction known as encoding layers and the second stage is to predictions and is named as decoding layers. Then the post-processing stage. It has done some morphological operations i.e. removing the scattered pixels. For the

CVC-CLINICDB data set, Our Proposed Method without Post-Process attains precision as 98.32%, and with Post-Process attains precision as 99% and recall as 82.7%.

Jovana Panic et al [32] implemented a CNN-based system for Colorectal cancer segmentation on MRI images. This is a new approach for the segmentation of colon cancer based on small-size ROI images. At first, preprocessing consists of 3 steps: the evaluation of the Apparent Diffusion Coefficient (ADC), the cropping phase, and the extraction of the ROIs. All cropped images are divided into regions of dimensions 3x3, 6x6, 9x9 without overlap. Those ROIs have been labeled in three different classes: tumoral ROI (label 2), bright tumoral ROI (label 1), and dark non-tumoral ROI (label 0). The three Convolutional layers are defined by a 3x3 kernel and the ReLU activation function. To analyze the effects of the resolution of the ROIs on the performances, three different CNN systems have been implemented as ROIs classifiers: one for the 3x3 ROIs, one for 6x6 ROIs, and the last one for 9x9ROIs. The dataset is divided into 80% for training and 20% for testing. This system has a DSC of 0.58%, a precision of 0.74%, and a recall of 0.54%for the validation set. These results prove that using a small dimensional ROI the classifiers are more precise since there is less in homogeneous information.

Anuja et al [33] implemented Colon Cancer Biopsy Image Analysis using Deep Learning methods. Here is a dataset from Kaggle (https://www.kaggle.com/kmader/colorectal-histologymnist) which contains data with different sizes of biopsy images. There are no preprocessing techniques applied to cancer images. It first implemented the CNN model using CSV file as input, which contains pixel values of the all 5000 images in a data set with (64*64) size. It takes 20 epochs. And then VGG16[11] is implemented then it has an accuracy of 72%. And then inception v3, here reduce the high computational overhead of the convolution layer by breaking the large convolution into smaller convolution. So it has the best accuracy among the other two. It gives 89% accuracy. That is when the custom layer changes then accuracy and complexity varies but inception v3 takes more time than others.

Akshay M Godkhindi et al [34] presented Automated Detection of Polyps in CT Colonography images using Deep Learning Algorithms in Colon Cancer Diagnosis. CT Colonoscopy Dataset is from “The cancer imaging archive” (TCIA), it contains 825 cases with an XLS sheet that contains polyp description and location within the colon segments. At first, each block is classified into type1 (usually ascending/ descending colon), colon type 2 (usually Transverse and sigmoid colon), and type 3 (noise). Then in preprocessing do some morphological operations and set a threshold for filtering the air-filled regions. Then find a region of interest and apply CNN. Then feature extraction by machine learning algorithms, Experiment is carried on the same dataset to extract LBP-HOG feature, then train and test on Random forest and k– nearest neighbor and also use Support Vector Machine (SVM), Logistic regression gives an accuracy of less than 75% and results showed the accuracy proposed method for colon segmentation using CNN (87%) out performs RF (85%) and KNN (83%). The polyp detection accuracy of CNN (88%) is better than Random forest (85%) and KNN (80%), also the Sensitivity of polyp detection using CNN (88%) is quite higher than RF (80%) and KNN (83%). Hence CNN has better for colon segmentation and polyp detection than RF and KNN.

International Journal of Advanced Research in Engineering Technology and Science ISSN 2349-2819
www.ijarets.org Volume-9, Issue-7 July – 2022 Email- editor@ijarets.org

Overview Of All The Deep Learning Techniques Used For The Detection And Segmentation Of Colonic Polyps

Sl No:	Author Name	Disease Diagnosed	Dataset Used	Algorithm or Method	Results
1	Xi Mo et al	Polyp Detection	CVC-Clinic CVC-Colon	FRCNN+VGG	Precision: 86.2%, Recall: 98.1% F1-score: 91.7%, F2-score: 95.6%.
2	Ashkan Tashk et al	Segmentation of colon polyp	ETIS-LARIB CVC-ColonDB	CNN+UNet	• With Post-Processing Accuracy:99.6%, Precision: 70.2%, Recall : 90.9% F1-Score:79.23%. • Without Post Process Accuracy:99.1%, Precision: 92.82%, Recall :77.67%, F1Score:84.57%
3	Sebastian Gross et al	Classification of Colon Polyps	Images acquired using an Olympus Exera II NBI zoom endoscopy	• Sequential Forward Feature Selection(SFFS) • Sequential Backward Feature Elimination (SBFE). • Probabilistic meta-heuristic Simulated Annealing (SA).	Simulated Annealing , Accuracy : 96.2% Sensitivity: 97.6%, Specificity: 94.2%
4	Isabel N. et al	Detection of Colon Polyps	Images produced by the PillCam Colon capsule	Chann- Vese's segmentation model	It does not do the complete segmentation it only detects the higher part of the polyp
5	Yao Yao et al	Classification and Segmentation in Colorectal Images	The anorectal department of a hospital in Shaanxi Province, China, under ethical approval.	Self-Paced Transfer Network-STVGG+VGG19	Accuracy : 96%
6	K.GayathriDevi et al	Segmentation of Colon in 3D CT Images and Removal of Opacified Fluid	The data downloaded from TCIA cancer imaging archive and on real data set	Cascade Feed Forward Neural Network+ Moore-Neighbor tracing algorithm	Accuracy : 98%, The Graph Cuts approach : 90.8% Level Sets : 97.6, Specificity value : 97%.
7	Sae Hwang et al	Automatic Polyp Region Segmentation	137 poly frames were selected	Watershed Algorithm and Ellipse Segmentation	Sensitivity :93% Specificity: 98%

8	Debesh et al	Dataset is used for segmentation,localization , and classification of polyps	Kvasir-SEG	Efficient FCM (unsupervised clustering algorithm) and deep-learning ResUNet architecture	FCM attains : Dicecoefficient:0.239002% A mean IoU: 0.314187%. ResUNet model attains Dicecoefficient:0.787 % mean IoU : 0.777771%
9	Hemin Ali et al.	Polyp Detection and Segmentation	CVCClinicDB, ETIS-Larib	Mask RCNN+Resnet50 +Resnet 101+Inception Resnet V3	Mask R-CNN with Resnet101achieved the highest Precision (80%) and Good recall (72.59%).
10	Debesh Jha et al	Real-Time Polyp Detection, Localisation, and Segmentation	Kvasir SEG	Detection and Segmentation (e.g., UNet, Faster R-CNN), speed (e.g., UNet withResNet34, YOLOv3), and accuracy (e.g., PSPNet, FCN8, or DoubleUNet) or acombination of all (e.g., DeepLabv3+, YOLOv4).+SOTA methods	UNet with ResNet34 and DeepLabv3+ backbone provided the best trade-off speed and accuracy over several SOTA methods.
11	Aparna Ratheesh et al	Polyp Detection and Density Estimation	Data set courtesy of the Medical college Hospital, Trivandrum. The database consists of endoscopic videos of 10 patients consists of 2100 frames.	Markovian Random Field+SVM	Accuracy : 96.7%.
12	Patrick Brandao1 et al	Polyp Segmentation in Colonoscopy	MICCAI 2015	(AlexNet, GoogleNet, and VGG) in FCN	FCN-VGG Precision :73.61% Recall:86.31%
13	Sean R. Stanek et al	Real-time capture and segmentation of endoscopy video	Capturing the video from the endoscope hardware as a series of 720 x 480 x 24 bits-per-pixel images	Grabber filter+FIFO buffer	Sensitivity:100% Specificity : 99%
14	Tsubasa Hirakawa et al	Segmentation of colorectal NBI endoscopic images	NBI Images	SVM-MRF	Probability takes values of 0,0.05... 0.95, 0.99.
15	Tamaki et al	NBI image falls on to which type of class	NBI images	Bag of visual word framework+ SIFT descriptors	System is not a label but is the posterior probability of type classes

16	Jaeyong Kang et al	Polyp Segmentation in Colonoscopy Images	CVC-ClinicDB ETIS-Larib CVC-ColonDB	Mask RCNN+ FRCNN+ Resnet50+Resnet101+ RPN	Precision : 77.92%, Recall : 76.25%, Interception over the union: 69.46%
17	Ashkan Tashk et al	Polyp Detection	CVC-CLINICDB	CNN+Unet	Without Post-Process Precision :98.32%, With Post-Process Precision :99.02% Recall : 82.7%.
18	Jovana Panic et al	Colorectal cancer segmentation on MRI images	The Candiolo Cancer Institute, FPO-IRCCS between October 2010 and February 2016.	CNN+ROI	DSC : 0.58%, Precision: 0.74%, Recall : 0.54%
19	Anuja et al	Colon Cancer Biopsy Image Analysis	Kaggle (colorectal-histologymnist)	CNN+VGG16 CNN+Inception V3	Accuracy : 72% Accuracy: 89%
20	Akshay M Godkhindi et al	Automated Detection of Polyps	The cancer imaging archive (TCIA)	CNN+LBP-HOG Random forest and k–nearest neighbor and also use Support Vector Machine (SVM), Logistic regression	Logistic regression accuracy of less than 75% the accuracy proposed method for colon segmentation using CNN (87%) outperforms RF (85%) and KNN (83%). The polyp detection accuracy of CNN (88%)is better than Random forest (85%) and KNN (80%), also the Sensitivity of polyp detection using CNN (88%) is quite higher than RF (80%) and KNN (83%).

III. Discussion

Artificial Intelligence is the branch of computer science that mimics taking actions and thinking like humans. Machine Learning is the type of AI which trains the system and to do impossible tasks for humans. The human brain consists of neurons that convey messages to the body like deep learning imitates the human brain for learning, understanding, and making decisions. It uses unstructured data but today itself we use supervised learning models such as CNN, MRCNN, etc but in the future, we use unsupervised learning techniques.

IV. Conclusion

In this study about Colorectal Cancer, 20 differently published papers are reviewed here using last 11year papers (2010-2021). Most of the papers are Deep Learning-Based and some are Machine Learning based. The Deep Learning Methods such as CNN and VGG16, Mask RCNN, Faster RCNN have better results and machine learning algorithms such as SVM, Random Forest, MRF, etc also are used mainly. In comparison with Machine Learning and Deep Learning, better results are found in terms of accuracy, precision, recall, etc are in Deep Learning Methods. Most of the methods are supervised so in the future more diverse analysis and study about unsupervised learning methods are popular.

VI. FUTURE SCOPE

For analysis of Colon cancer and polyp, some new deep learning and machine learning techniques are used, and also the combination of deep learning techniques are used to attain better segmentation and classification of Colorectal Cancer.

VII. Reference

[1] Redmon, Joseph, Santosh Divvala, Ross Girshick, and Ali Farhadi. "You only look once: Unified, real-time object detection." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 779-788. 2016.

[2] Ren, Shaoqing, Kaiming He, Ross Girshick, and Jian Sun. "Faster r- cnn: Towards real- time object detection with region proposal networks In IEEE Transactions on Pattern Analysis and Machine Intelligence (pp. 1137–1149)." Los Alamitos, CA: IEEE 10 (2017).

[3] He, Kaiming, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. "Mask r-cnn." In Proceedings of the IEEE international conference on computer vision, pp. 2961-2969. 2017.

[4] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." In International Conference on Medical image computing and computer-assisted intervention, pp. 234-241. Springer, Cham, 2015.

[5] Badrinarayanan, Vijay, Alex Kendall, and Roberto Cipolla. "Segnet: A deep convolutional encoder-decoder architecture for image segmentation." IEEE transactions on pattern analysis and machine intelligence 39, no. 12 (2017): 2481-2495.

[6] Mo, Xi, Ke Tao, Quan Wang, and Guanghui Wang. "An efficient approach for polyps detection in endoscopic videos based on faster R-CNN." In 2018 24th international conference on pattern recognition (ICPR), pp. 3929-3934. IEEE, 2018.

[7] Tashk, Ashkan, Jürgen Herp, Esmaeil Nadimi, and Suddansk Universitet SDU. "Automatic Segmentation of Colorectal Polyps based on a Novel and Innovative Convolutional Neural Network Approach." WSEAS Transactions on Systems and Control, Vpl 14 (2019): 384-391.

[8] Gross, Sebastian, Stephan Palm, Jens JW Tischendorf, Alexander Behrens, Christian Trautwein, and Til Aach. "Automated classification of colon polyps in endoscopic image data." In Medical Imaging 2012: Computer-Aided Diagnosis, vol. 8315, p. 83150W. International Society for Optics and Photonics, 2012.

[9] Figueiredo, Isabel N., Surya Prasath, Yen-Hsi R. Tsai, and Pedro N. Figueiredo. "Automatic detection and segmentation of colonic polyps in wireless capsule images." ICES REPORT (2010): 10-36.

[10] Yao, Yao, Shuiping Gou, Ru Tian, Xiangrong Zhang, and Shuixiang He. "Automated Classification and Segmentation in Colorectal Images Based on Self-Paced Transfer Network." BioMed Research International 2021 (2021).

[11] Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv:1409.1556 (2014).

[12] Gayathri Devi, K., and R. Radhakrishnan. "Automatic segmentation of colon in 3D CT images and removal of opacified fluid using cascade feed forward neural network." Computational and mathematical methods in medicine 2015 (2015).

[13] Hwang, Sae, JungHwan Oh, Wallapak Tavanapong, Johnny Wong, and Piet C. De Groen. "Automatic polyp region segmentation for colonoscopy images using watershed algorithm and ellipse segmentation." In Medical Imaging 2007: Computer-Aided Diagnosis, vol. 6514, p. 65141D. International Society for Optics and Photonics, 2007.

[14] Jha, Debesh, Pia H. Smedsrud, Michael A. Riegler, Pål Halvorsen, Thomas de Lange, Dag Johansen, and Håvard D. Johansen. "Kvasir-seg: A segmented polyp dataset." In International Conference on Multimedia Modeling, pp. 451-462. Springer, Cham, 2020.

[15] Qadir, Hemin Ali, Younghak Shin, Johannes Solhusvik, Jacob Bergsland, Lars Aabakken, and Ilangko Balasingham. "Polyp detection and segmentation using mask R-CNN: Does a deeper feature extractor cnn always perform better?." In 2019 13th International Symposium on Medical Information and Communication Technology (ISMICT), pp. 1-6. IEEE, 2019.

[16] He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. 2016.

[17] Szegedy, Christian, Sergey Ioffe, Vincent Vanhoucke, and Alexander A. Alemi. "Inception-v4, inception-resnet and the impact of residual connections on learning." In Thirty-first AAAI conference on artificial intelligence. 2017.

[18] Jha, Debesh, Sharib Ali, Nikhil Kumar Tomar, Håvard D. Johansen, Dag Johansen, Jens Rittscher, Michael A. Riegler, and Pål Halvorsen. "Real-Time Polyp Detection, Localization and Segmentation in Colonoscopy Using Deep Learning." Ieee Access 9 (2021): 40496-40510.

[19] Huang, Gao, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q. Weinberger. "Densely connected convolutional networks." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 4700-4708. 2017.

[20] Chen, Liang-Chieh, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. "Encoder-decoder with atrous separable convolution for semantic image segmentation." In Proceedings of the European conference on computer vision (ECCV), pp. 801-818. 2018.

[21] Ratheesh, Aparna, and DEVIKA RG. "Efficient Method for Polyp Detection and Density Estimation Using MRF Segmentation in Colon Endoscopy." IJIIE-International Journal of Innovations & Implementations in Engineering 1 (2016): 2454-3489.

[22] Brandao, Patrick, Evangelos Mazomenos, Gastone Ciuti, Renato Caliò, Federico Bianchi, Arianna Menciassi, Paolo Dario, Anastasios Koulaouzidis, Alberto Arezzo, and Danail Stoyanov. "Fully convolutional neural networks for polyp segmentation in colonoscopy." In Medical Imaging 2017: Computer-Aided Diagnosis, vol. 10134, p. 101340F. International Society for Optics and Photonics, 2017.

[23] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." In Advances in neural information processing systems, pp. 1097-1105. 2012.

[24] Szegedy, Christian, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. "Going deeper with convolutions." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1-9. 2015.

[25] Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 3431-3440. 2015.

[26] Stanek, Sean R., Wallapak Tavanapong, Johnny S. Wong, JungHwan Oh, and Piet C. De Groen. "Automatic real-time capture and segmentation of endoscopy video." In Medical Imaging 2008: PACS and Imaging Informatics, vol. 6919, p. 69190X. International Society for Optics and Photonics, 2008.

[27] Hirakawa, Tsubasa, Tom Tamaki, Bisser Raytchev, Kazufumi Kaneda, Tetsushi Koide, Yoko Kominami, Shigeto Yoshida, and Shinji Tanaka. "SVM-MRF segmentation of colorectal NBI endoscopic images." In 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 4739-4742. IEEE, 2014.

[28] Tamaki, Toru, Junki Yoshimuta, Misato Kawakami, Bisser Raytchev, Kazufumi Kaneda, Shigeto Yoshida, Yoshito Takemura, Keiichi Onji, Rie Miyaki, and Shinji Tanaka. "Computer-aided colorectal tumor classification in NBI endoscopy using local features." Medical image analysis 17, no. 1 (2013): 78-100.

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

[30] Girshick, Ross, Jeff Donahue, Trevor Darrell, and Jitendra Malik. "Rich feature hierarchies for accurate object detection and semantic segmentation." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 580-587. 2014.

[31] Tashk, Ashkan, Jürgen Herp, and Esmaeil Nadimi. "Fully Automatic Polyp Detection Based on a Novel U-Net Architecture and Morphological Post-Process." In 2019 International Conference on Control, Artificial Intelligence, Robotics & Optimization (ICCAIRO), pp. 37-41. IEEE, 2019.

[32] Panic, Jovana, Arianna Defeudis, Simone Mazzetti, Samanta Rosati, Giuliana Giannetto, Lorenzo Vassallo, Daniele Regge, Gabriella Balestra, and Valentina Giannini. "A Convolutional Neural Network based system for Colorectal cancer segmentation on MRI images." In 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), pp. 1675-1678. IEEE, 2020.

[33] Anuja A. Ubale, S. G. Shikalpure. "Colon Cancer Biopsy Image Analysis using Deep Learning." IJRTE-International Journal of Recent Technology and Engineering (Volume-8 Issue-2, July 2019): 2277-3878.

[34] Godkhindi, Akshay M., and Rajaram M. Gowda. "Automated detection of polyps in CT colonography images using deep learning algorithms in colon cancer diagnosis." In 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), pp. 1722-1728. IEEE, 2017.