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A Literature Survey on Computer-Aided Diagnosis in Detection and Classification of Polyp in Colon Cancer using CT Colonography

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Abstract: Colorectal cancer is a cancer that starts inside the colon or the rectum in large intestine. These cancers is likewise called colon cancer or rectal cancer, depending on wherein they start. Colon and rectal cancer are frequently grouped together because they've many features in common and most colorectal cancers begin as a increase on the internal lining of the colon or rectum called a polyp. A few types of polyps can change into cancer over the several years, but not all polyps end up in cancers. The risk of changing into a most cancers depends at the kind of polyp. Computer-aided detection (CADe) and analysis (CAD) has been a rapidly growing, potential area of research in medical imaging. Machine leaning (ML) plays a crucial role in CAD, because objects such as lesions and organs may not be represented accurately with the aid of an easy equation; as a consequence, medical pattern recognition essentially require "getting to know from examples." Computed tomography (CT) Colonography or virtual colonoscopy makes use of special x-ray machine to have a look at the large intestine for cancer and growths known as polyps. All through the examination, a small tube is inserted a short distance into the rectum to permit for inflation with air at the same time as CT image of the colon and the rectum are taken. CT technologist determines those images to discover the severity of polyp based on its length. In this survey, we review the different papers and journals in the literature that attempted to address these problems and compare various pre-processing steps, classification and segmentation algorithms, feature set considered, which are used to detect and classify polyp in colon cancer and we also focus on various deep learning algorithms used in similar medical diagnosis and how efficiently it is used to solve problem.

Keywords: Colorectal cancer, Computed tomography (CT) Colonography, polyp, Deep learning Algorithms.

I. INTRODUCTION

This Colorectal cancer is the third most commonly diagnosed cancer and the third leading cause of cancer death in both men and women in the US. The American Cancer Society estimates that 136,830 people will be diagnosed with colorectal cancer and 50,310 people will die from the disease in 2014.

The majority of these cancers and deaths could be prevented by applying existing knowledge about cancer prevention, increasing the use of recommended screening tests, and ensuring that all patients receive timely, standard treatment. The colon has 4 sections:

The first section is called the ascending colon; it begins with a pouch called the cecum, where undigested food is received from the small intestine, and extends upward on the right side of the abdomen. The second section is called the transverse colon because it crosses the body from the right to the left side. The third section is called the descending colon because it descends on the left side.

The fourth section is called the sigmoid colon because of its "S" shape; the sigmoid colon joins the rectum, which connects to the anus.

Colorectal cancer develops in the colon or the rectum, also known as the large intestine (Figure 1). The colon and rectum are parts of the digestive system, also called the gastrointestinal (GI) system. The digestive system processes food for energy and rids the body of solid waste (fecal matter or stool). After food is chewed and swallowed, it travels through the oesophagus to the stomach.

There it is partially broken down and sent to the small intestine, where digestion continues and most of the nutrients are absorbed. Cancer develops much less often in the small intestine than in the colon or rectum (colorectum). The small intestine joins the large intestine in the lower right abdomen. The small and large intestine are sometimes called the small and large bowel. The first

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and longest part of the large intestine is the colon, a muscular tube about 5 feet long. Water and mineral nutrients are absorbed from the food matter in the colon. Waste (feces) left from this process passes into the rectum, the final 6 inches of the large intestine, and is then expelled from the anus. Colorectal cancer usually develops slowly, over a period of 10 to 20 years.5 Most begin as a noncancerous growth called a polyp that develops on the inner lining of the colon or rectum. The most common kind of polyp is called an adenomatous polyp or adenoma. Adenomas arise from glandular cells, which produce mucus to lubricate the colorectum. An estimated one-third to one-half of all individuals will eventually develop one or more adenomas. Although all adenomas have the capacity to become cancerous, fewer than 10% are estimated to progress to invasive cancer. The 2 main types of polyps are: Adenomatous polyps (adenomas): These polyps sometimes change into cancer. Because of this, adenomas are called a pre-cancerous condition. Hyperplastic polyps and inflammatory polyps: These polyps are more common, but in general they are not pre-cancerous. Dysplasia, another pre-cancerous condition, is an area in a polyp or in the lining of the colon or rectum where the cells look abnormal (but not like true cancer cells) [1]. Screening for colorectal cancer lessens the risk of dying from that disease [2].

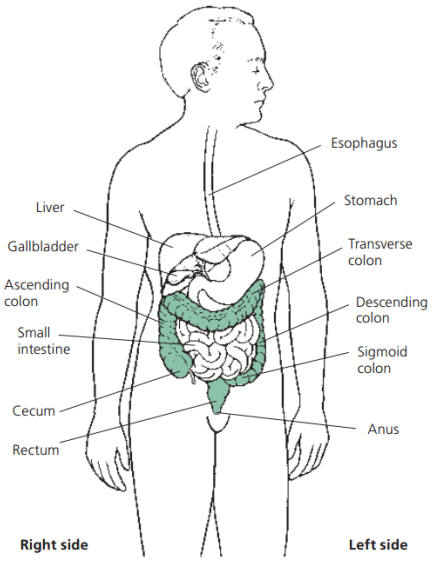

Fig. 1. Anatomy of the Colon and Rectum [1]

Computed tomography (Fig.2.) , more commonly known as a CT or CAT scan, is a diagnostic medical test that, like traditional x-rays, produces multiple images or pictures of the inside of the body. The cross-sectional images generated during a CT scan can be reformatted in multiple planes, and can even generate three-dimensional images. These images can be viewed on a computer monitor, printed on film or transferred to a CD or DVD. CT images of internal organs, bones, soft tissue and blood vessels typically provide greater detail than traditional x-rays, particularly of soft tissues and blood vessels. CT Colonography, also known as virtual colonoscopy, uses low dose radiation CT scanning to obtain an interior view of the colon (the large intestine) that is otherwise only seen with a more invasive procedure where an endoscope is inserted into the rectum and passed through the entire colon. The major reason for performing CT Colonography is to screen for polyps or cancers in the large intestine. Polyps are growths that arise from the inner lining of the intestine. A very small number of polyps may grow and turn into cancers. The goal of screening with CT Colonography is to find these growths in their early stages, so that they can be removed before cancer has had a chance to develop.

The American Cancer Society (ACS) recommends that women and men undergo screening for colon cancer or polyps beginning at age 50. As part of its recommendation, ACS suggests CT Colonography as an option once every five years. Individuals at increased risk or with a family history of colon cancer may start screening at age 40 or younger and may be screened at shorter intervals (for example, having a colonoscopy every five years). Risk factors for the disease include a history of polyps or having a family history of colon cancer. [5] Studies have indicated that less than 5% of adenomatous polyps progress into carcinomas. However, clinical studies suggest that over 95% of colorectal carcinomas arise from these slow-growing, adenomatous polyps. Consequently, polypectomy of colorectal adenomas was shown to reduce the incidence of CRC by nearly 80. Progression of an adenoma into cancer can be predicted by size, villous histology, degree of dysplasia, and inherited or environmental factors.

The risk of a polyp being cancerous increases as the size of the polyp increases. A study found that there is only a 1.3% risk that a polyp that is less than 10-mm is a carcinoma. In comparison, a polyp 10-mm to 20-mm in size has a 9.5% chance of malignancy and a polyp greater than 20-mm has a 46% chance of malignancy. Polypectomy of polyps that are at least 5-mm (12), 6-mm to 8-mm (13–15), or 10-mm (16) have been suggested by various experts. The progression of an adenoma into a carcinoma is predicted to take about 10 years [7]

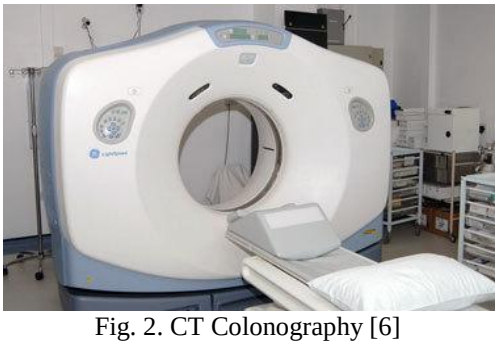

Fig. 2. CT Colonography [6]

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The image set of particular patient's obtained from CT Colonography is annotated by CT technologist to find polyps in it and classify its type. As the technologist and experts are needed to detect polyps, it's very hard for people in remote areas (rural areas) in developing and underdeveloped countries to connect the experts every time. Due to lack of experts and automated tool, the pre-cancerous and cancerous cells goes undetected in particular time span and ultimately causes death of patient. Hence there is need of advanced automated tool in detecting polyps and classify according to its size and access it risk, pre-cancerous and cancerous cells from CT Colonography images.

II. LITERATURE SURVEY

Excluding skin cancers, colorectal cancer is the third most common cancer diagnosed in both men and women in the United States. The American Cancer Society's estimates for the number of colorectal cancer cases in the United States for 2016 are: 95,270 new cases of colon cancer and 39,220 new cases of rectal cancer. Overall, the lifetime risk of developing colorectal cancer is: about 1 in 21 (4.7%) for men and 1 in 23 (4.4%) for women. This risk is slightly lower in women than in men. A number of other factors (described in colorectal cancer risk factors) can also affect your risk for developing colorectal cancer. Colorectal cancer is the third leading cause of cancer-related deaths in the United States when men and women are considered separately, and the second leading cause when both sexes are combined. It is expected to cause about 49,190 deaths during 2016. The death rate (the number of deaths per 100,000 people per year) from colorectal cancer has been dropping in both men and women for several decades. There are a number of likely reasons for this. One is that colorectal polyps are now being found more often by screening and removed before they can develop into cancers or are being found earlier when the disease is easier to treat [3].

Almost 60% of cases are encountered in developed countries. The number of CRC-related deaths is estimated to be approximately 608000 worldwide, accounting for 8% of all cancer deaths and making CRC the fourth most common cause of death due to cancer.
In India, the annual incidence rates (AARs) for colon cancer and rectal cancer in men are 4.4 and 4.1 per 100000, respectively. The AAR for colon cancer in women is 3.9 per 100000. Colon cancer ranks 8th and rectal cancer ranks 9th among men. For women, rectal cancer does not figure in the top 10 cancers, whereas colon cancer ranks 9th. In the 2013 report, the highest AAR in men for CRCs was recorded in Thiruvananthapuram (4.1) followed by Bangalore (3.9) and Mumbai (3.7). The highest AAR in women for CRCs was recorded in Nagaland (5.2) followed by Aizawl (4.5) [4].

TABLE I
CLASSIFICATION AND DETECTION OF POLYP USING CT COLONOGRAPHY USED IN VARIOUS RESEARCH PAPERS.

Author	Dataset	Classifier/Methods/Algorithms	Result/Performance
Yuichi Motai et al. [8]	CT colonography data of 146 patients	novel method – Predictive LACK	Computation time for nonstationary learning is reduced by 33% compared with stationary learning.
Yifan Hu et al. [9]	384 polyp datasets, of which 52 are non-neoplastic polyps and the rest are neoplastic polyps	Haralick's 3D model, KL transform, Random Forest (RF) for classification	AUC = 0.8016
Xiaoyun Yang et al. [10]	52 CTC volumes from five different institutions in Europe and the USA.	novel region-level colon segmentation method	Jaccard Index – 79.30%
Kenji Suzuki et al.[11]	biopsy-confirmed 54 neoplastic lesions in 29 patients and 14 non-neoplastic lesions in 10 patients	shape-index-based coarse segmentation of lesions, 3D volume growing and sub-voxel refinement for fine segmentation of lesions, , Wilks' lambda-based stepwise feature selection, linear	AUC = 0.82

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		discriminant analysis for providing an integrated imaging biomarker for diagnosis of neoplastic lesions	
Manjunath et al.[12]	40 patient's dataset	adaptive smoothing for de-noising the colon lumen by preserving the edges, the canny operator for colon boundary recognition, connected component labelling for colon segments delineation and prominently, the translation of Radiologist's perspective of colon assessment on axial slices in to the decision making system	2 minutes for segmenting 500 CTC images. The average accuracy was 93.675±0.3224%. with respect to segmentation
Ming Ma et al.[13]	First dataset includes 49 CTC scans of 25 patients and the second dataset encompasses 86 scans of 53 patients.	MAP-EM segmentation for VM extraction. Random Forest RF based classification with feature selection,	AUC = 0.9242 for classification
Ming Ma et al. [14]	CTC database from 25 patients with 49 CT scans which were acquired using multi-slice CT scanners	Multiple kernel learning (MKL) with adaptive kernel method for CAD of colonic polyps, called AKMKL method.	AK-MKL method achieves better performance, compared with MKL and AK-SVM method.
Kenji Suzuki [15]	100 patient cases consisting of 200 CT colonography datasets acquired at the University of Chicago Medical Centre	Wilks' lamda-based, combining classifiers – fusing classifiers, or ensemble training. Fusing methods include Bagging, boosting, and Adaboost.	Ensamble of expert patch/pixel-based MLs, the falsepositive rate of our original CAD system was improved from 4.9 to 2.2 (222/100) per patient at a by-polyp sensitivity of 96% (25/26) (by-patient sensitivity of 100%)
Jian-Wu Xu et al. [16]	University of Chicago Medical Centre. The database of 206 CTC datasets obtained from 103 patients with colonic-polyp database (25 polyps and 2624 nonpolyps).	feature selection method based on a sequential forward floating selection (SFFS) procedure to improve the performance of a classifier in computerized detection of polyps in CT colonography (CTC) nonlinear support vector machine (SVM) classifier	ACCU – 83.9%
Yifan Hu et al. [16]	Walter Reed Army Medical Center (WRAMC), CTC	Two "mixture" classifiers, one is the combination of two	AUC value of 0.8546

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	database of 114 scans from 67 patients with polyps of sizes larger than 8 mm colon polyp database including 116 neoplastic lesions and 37 hyperplastic lesions.	among the SVM, RF and LDA, and the other is the combination of all three.	
Yifan Hu et al. [17]	CTC database of 114 scans from 67 patients with polyps of sizes larger than 8 mm	to minimize the spatial variation in expanding the well-known Haralick texture descriptor in three-dimensional (3D) space for extraction and selection of volumetric texture features , perform one kind of principal component (PC) analyses, i.e., the Karhunen-Loeve transform, on the 13 directions and select the features along the PCs, instead of the mean and range. RF classifier	AUC of 0.8725
Toru Tamaki et al. [18]	908 NBI images Endoscopic	local features followed by Support Vector Machine (SVM) classifiers.	AUC 93%
D. S.V.G.K.Kaladhar et al.[19]	The Notterman Carcinoma dataset is used from gene expression project of Princeton University,	Colon Cancer dataset showed that Logistics, Ibk, Kstar, NNge, ADTree, Random Forest Algorithms are the best suited algorithms for the classification analysis and Hierarchical Clustering method is used for the clustering analysis.	Random Forest Algorithms show 100 % correctly classified instances, followed by Navie Bayes and PART with 97.22 %, Simple Cart and ZeroR has shown the least with 50 % of correctly classified instances.
Hongbin Zhu et al. [20]	15 CTC scans, among which 12 are from the University of Wisconsin Hospital and Clinics, and the rest from the public Water Reeds Army Medical Center (WRAMC) database	LS-Based Fold Segmentation	Compared to the expert-drawn folds on 15 patient scans, the experimental results have shown that 92.7% of all folds are successfully detected with very few false positives
Xin Xiong et al [21]	CT colonography imbalanced polyp data sets	cascade-Adaboost framework	overall per-polyp sensitivity of 90% (for polyps' diameter 5 mm and greater), with false positives of 6 per volume on average.

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Bowen Song et al. [22]	CTC database of 110 scans from 56 patients, 148 lesions where 35 are non-neoplastic and 113 are neoplastic lesion	3D Haralick Texture Model, support vector machine (SVM) classifier	AUC = 0.852
Shijun Wang et al. [23]	CTC data set obtained from 50 patients from three medical centers	multiple-instance learning (MIL)	proposed method showed significantly better performance compared with several traditional MIL methods
Shijun Wang et al. [24]	CT colonography dataset containing 50 patients.	Auxiliary variables to rank training samples	ACC = 0.8347
Jiamin Liu et al. [25]	prediction performance was evaluated on 134 polyps by comparing the predicted with the true polyp locations at OC	Minimal-energy curve method.	accurately predict polyp locations at OC to within±0.5 colonoscope mark (5 cm) for more than 58% of polyps and to within ±1 colonoscope mark (10 cm) for more than 96% of polyps
Tarik A. Chowdhury et al. [26]	99 patient datasets	26-neighbourhood region growing algorithm	It takes 16.29 second to segment the colon from an abdomen CT dataset. Sensitivity (sen.) / 98.04% and 99.59% Surface area detection (SAD)
C Robinson et al. [27][27]	137 cancers patient images	CAD algorithm	CAD identified Of 124 (90.5%), 122 (89.1%), 119 (86.9%) and 102 (74.5%) at a sphericity of 0, 50, 75 and 100, respectively
Kenji Suzuki et al. [28]	NYU Medical Center (NYU) and the Cleveland Clinic Foundation (CCF). 246 CTC datasets obtained from 123 patients, each of whom was scanned in both supine and prone positions.	pattern-recognition technique based on the use of an artificial neural network (ANN) as a filter, which is called a massive-training ANN (MTANN),	LAP-MTANN (0.84) was slightly higher than that of the original MTANN (0.82) with no statistically significant difference.
L.Bogoni et al. [29]	The database consisted of 150 datasets, 292 volumes from high-resolution CT scanners. These included both patients with polyps (positive cases) (n=64) and patients without polyps (negative cases) (n=86)	Colon CAD algorithm	The sensitivity for middle to large sized polyps is on the average 90% while the overall sensitivity is roughly 82%. The false positive rate is a manageable 4.5 per volume on average.

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Anna K. Jerebko et al. [30]	Polyp database obtained from 80 studies that included supine and prone CT colonographic images of 40 patients.	Back-propagation NNs trained with the Levenberg-Marquardt algorithm were used as primary classifiers, set of features included region density, Gaussian and mean curvature and sphericity, lesion size, colon wall thickness, and the means and standard deviations of all of these values.	The overall sensitivity and specificity were 82.9% and 95.3%, respectively,
Janne Nappi et al. [31]	88 CT colonography datasets	Knowledge-Guided Segmentation, Anatomy-Based Extraction	dataset-based false-positive rate of the automated polyp detection was improved by 10% without compromising the 100% case-based sensitivity

Table 1 represents the brief description of various recent research paper, dataset size, classification methods, Algorithms used and results.
In [33] Mohammad Havaei., et al. presents a fully automatic brain tumor segmentation method based on Deep Neural Networks (DNNs). The proposed networks are tailored to glioblastomas (both low and high grade) pictured in MR images. By their very nature, these tumors can appear anywhere in the brain and have almost any kind of shape, size, and contrast. Here, authors give a description of different model choices that we've found to be necessary for obtaining competitive performance.

Author explore in particular different architectures based on Convolutional Neural Networks (CNN), i.e. DNNs specifically adapted to image data. A novel CNN architecture which differs from those traditionally used in computer vision is presented. Proposed CNN exploits both local features as well as more global contextual features simultaneously. Also, different from most traditional uses of CNNs, our networks use a final layer that is a convolutional implementation of a fully connected layer which allows a 40 fold speed up. Author also describe a 2-phase training procedure that allows us to tackle difficulties related to the imbalance of tumor labels. Finally, explore a cascade architecture in which the output of a basic CNN is treated as an additional source of information for a subsequent CNN.

Results reported on the 2013 BRATS test dataset reveal that our architecture improves over the currently published state-of-the-art while being over 30 times faster.

In [34], Vibhu & Clayton proposed Preventive care recommendations for breast cancer require that women above a certain age be regularly screened by mammography [1, 2]. Computer aided interpretation of mammograms involves the extraction of features of suspicious areas in the mammograms and providing these as inputs to a clinical decision support system. While the extraction of computational features (such as geometry, contrast, intensity, texture) from a given region of the image may be easily automated, extraction of semantic features (for instance the type of lesion and its pathology) has traditionally relied on radiologists documenting their findings in structured or free format text. Deep convolutional neural networks have demonstrated the ability to outperform skilled humans in certain observational tasks [3, 4]. In proposed study, we investigate the feasibility of training a convolutional neural network with annotated lesion images drawn from the Digital Database for Screening Mammography (DDSM). Author report results on two label prediction tasks that influence mammogram interpretation and downstream clinical actions related to diagnosis, intervention and prognosis. Here we examine the application of a purely data driven approach to the task of predicting semantic features, using a corpus of annotated images for training our predictor. Author examine the application of a purely data driven approach to the task of prediction of semantic features as a means of improving overall efficacy of screening mammogram and ultimately improving the clinical care for breast cancer patients.

In [35], Fausto Milletari., et al. proposed an approach to 3D image segmentation based on a volumetric, fully convolutional neural network (CNN). CNN is trained end-to-end on MRI volumes depicting prostate, and learns to predict segmentation for the whole volume at once. Author proposes a novel objective function that is optimized during training, based on Dice coefficient. In this way problem can deal with situations where there is a strong imbalance between the number of foreground and background voxels. To cope with the limited number of

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annotated volumes available for training, we augment the data applying random non-linear transformations and histogram matching. Author show in experimental evaluation that proposed approach achieves good performances on challenging test data while requiring only a fraction of the processing time needed by other previous methods.

III. CONCLUSION AND FUTURE SCOPE

Literature review from various papers in journals published from different sources is presented in this paper. The different techniques, methods and algorithms are proposed by many researchers in detecting lesions and polyps using segmentation and classifying its type. From several paper we can infer that preprocessing step is the basic and very important step for improving overall accuracy.

The dataset from various sources are taken and to mention in particular, The Cancer Imaging Archive (TCIA) provides the large dataset images on colon cancer with ground truth information. Wide variety of feature set are considered and to node improvement in the feature set has the large impact in classification accuracy. We also infer segmentation is the very crucial and difficult task in CT colonography as raw images are less informative and lot of Image processing is required. Most of the researchers have considered the size of the polyp for classifying the severity of colon cancer.

The various classical machine learning algorithms have been applied for classification and have reached the accuracy which is quite acceptable. Only few researchers have proposed the deep learning technique (Artificial Neural network) for classification and segmentation of cervical cancer and have mentioned scope in future research. We have also explored similar medical image diagnosis like Brain tumor detection and breast cancer detection which have successfully explored deep neural network such as convolution neural network (CNN) for image segmentation and classification. Hence we conclude that there is lot of scope in exploring the deep learning algorithms like (CNN) for tackling the above problem and explore the present feature set and enhancing as per the requirements of algorithms.

REFERENCES

[1] ColorectalCancerFacts&Figures:http://www.cancer.org/research/cancerfactsstatistics/colorectal-cancer-facts-figures
[2] Anderson, William F., Kate Z. Guyton, Robert A. Hiatt, Sally W. Vernon, Bernard Levin, and Ernest Hawk. "Colorectal cancer screening for persons at average risk." Journal of the National Cancer Institute 94, no. 15 (2002): 1126-1133.
[3] American Cancer Society. Cancer Facts & Figures 2016, American Cancer Society, 2016.
[4] ColorectalCancerIndianCouncilofMedicalResearchwww.icmr.nic.in/guide/cancer/Colorectal/Colorectal%20Cancer.pdf
[5] CTColonographyhttp://www.radiologyinfo.org/en/info.cfm?pg=ct_colo
[6] Cancer Research UK : http://www.cancerresearchuk.org/about-cancer/cancers-in-general/tests/ct-colonography
[7] Frentz, Suzanne M., and Ronald M. Summers. "Current status of CT colonography." Academic radiology 13, no. 12 (2006): 1517.
[8] Motai, Yuichi, Dingkun Ma, and Hiroyuki Yoshida. "Smart Anomaly Prediction in Non-stationary CT Colonography Screening."
[9] Hu, Yifan, Zhengrong Liang, Bowen Song, Hao Han, Perry J. Pickhardt, Wei Zhu, Chaijie Duan, Hao Zhang, Matthew A. Barish, and Chris E. Lascarides. "Texture Feature Extraction and Analysis for Polyp Differentiation via Computed Tomography Colonography." IEEE transactions on medical imaging 35, no. 6 (2016): 1522-1531.
[10] Yang, Xiaoyun, Xujiong Ye, and Greg Slabaugh. "Multilabel region classification and semantic linking for colon segmentation in CT colonography." IEEE Transactions on Biomedical Engineering 62, no. 3 (2015): 948-959.
[11] Suzuki, Kenji, Mohammadamin Zarshenas, Junchi Liu, Yonghui Fan, Nazanin Makkinejad, Paul Forti, and Abraham H. Dachman. "Development of Computer-Aided Diagnostic (CADx) System for Distinguishing Neoplastic from Nonneoplastic Lesions in CT Colonography (CTC): Toward CTC beyond Detection." In Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on, pp. 2262-2266. IEEE, 2015.
[12] Manjunath, K. N., K. Gopalakrishna Prabhu, and P. C. Siddalingaswamy. "A knowledge based approach for colon segmentation in CT colonography images." In 2015 IEEE International Conference on Signal and Image Processing Applications (ICSIPA), pp. 65-70. IEEE, 2015.
[13] Ma, Ming, Huafeng Wang, Bowen Song, Yifan Hu, Xianfeng Gu, and Zhengrong Liang. "Random forest based computer-aided detection of polyps in CT colonography." In 2014 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC), pp. 1-4. IEEE, 2014.
[14] Ma, Ming, Huafeng Wang, Bowen Song, Yifan Hu, Xianfeng Gu, and Zhengrong Liang. "Multiple kernel learning with adaptive kernel method for computer-aided detection of colonic polyps." In 2014 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC), pp. 1-5. IEEE, 2014.
[15] Suzuki, Kenji. "Mining of Training Samples for Multiple Learning Machines in Computer-Aided Detection of Lesions in CT Images." In 2014 IEEE International Conference on Data Mining Workshop, pp. 982-989. IEEE, 2014.
[16] Xu, Jian-Wu, and Kenji Suzuki. "Max-AUC feature selection in computer-aided detection of polyps in CT colonography." IEEE journal of biomedical and health Hu, Yifan, Bowen Song, Ming Ma, and Zhengrong Liang. "A mixture classifier for computer aided diagnosis of polyp malignancy for CT colonography." In 2014 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC), pp. 1-5. IEEE, 2014.
[17] Hu, Yifan, Bowen Song, Ming Ma, and Zhengrong Liang. "An application of KL transform in feature extraction and selection for polyp differentiation via CT colonography." In 2014 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC), pp. 1-5. IEEE, 2014.
[18] 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.
[19] Kaladhar, D. S. V. G. K., Bharath Kumar Pottumuthu, Padmanabhuni V. Nageswara Rao, Varahalarao Vadlamudi, A. Krishna Chaitanya, and R. Harikrishna Reddy. "The Elements of Statistical Learning in Colon Cancer Datasets: Data Mining, Inference and Prediction." Algorithms Research 2, no. 1 (1926): 8-17.
[20] Zhu, Hongbin, Matthew Barish, Perry Pickhardt, and Zhengrong Liang. "Haustral fold segmentation with curvature-guided level set evolution." IEEE Transactions on Biomedical Engineering 60, no. 2 (2013): 321-331.
[21] Xiong, Xin, Li-sheng Xu, Bao-lin Mao, Xiao-zhao Chen, and Yan Kang. "Fast and robust polyp detection in CT colonography." In

ISSN (Online) 2278-1021
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IJARCCE

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ICRITCSA

M S Ramaiah Institute of Technology, Bangalore

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Medical Imaging Physics and Engineering (ICMIPE), 2013 IEEE International Conference on, pp. 57-60. IEEE, 2013.

[22] Song, Bowen, Guopeng Zhang, Huafeng Wang, Fangfang Han, Wei Zhu, Hongbing Lu, and Zhengrong Liang. "A feasibility study of high order texture features with application to pathological diagnosis of colon lesions for CT Colonography." In 2013 IEEE Nuclear Science Symposium and Medical Imaging Conference (2013 NSS/MIC), pp. 1-5. IEEE, 2013.

[23] Wang, Shijun, Matthew T. McKenna, Tan B. Nguyen, Joseph E. Burns, Nicholas Petrick, Berkman Sahiner, and Ronald M. Summers. "Seeing is believing: Video classification for computed tomographic colonography using multiple-instance learning." IEEE transactions on medical imaging 31, no. 5 (2012): 1141-1153.

[24] Wang, Shijun, Matthew McKenna, Nicholas Petrick, Berkman Sahiner, Marius G. Linguraru, Zhuoshi Wei, Jianhua Yao, and Ronald M. Summers. "ROC-like optimization by sample ranking: application to CT colonography." In 2012 9th IEEE International Symposium on Biomedical Imaging (ISBI), pp. 478-481. IEEE, 2012.

[25] Liu, Jiamin, Kevin W. Chang, Jianhua Yao, and Ronald M. Summers. "Predicting polyp location on optical colonoscopy from CT colonography by minimal-energy curve modeling of the colonoscope path." IEEE Transactions on Biomedical Engineering 59, no. 12 (2012): 3531-3540.

[26] Chowdhury, Tarik A., and Paul F. Whelan. "A fast and accurate method for automatic segmentation of colons at CT colonography based on colon geometrical features." In Machine Vision and Image Processing Conference (IMVIP), 2011 Irish, pp. 94-100. IEEE, 2011.

[27] Robinson, C., S. Halligan, G. Iinuma, W. Topping, S. Punwani, L. Honeyfield, and S. A. Taylor. "CT colonography: computer-assisted detection of colorectal cancer." The British journal of radiology (2014).

[28] Suzuki, Kenji, Jun Zhang, and Jianwu Xu. "Massive-training artificial neural network coupled with Laplacian-eigenfunction-based dimensionality reduction for computer-aided detection of polyps in CT colonography." IEEE Transactions on medical imaging 29, no. 11 (2010): 1907-1917.

[29] Bogonia, L., P. Cathiera, M. Dundara, A. Jerebkoa, S. Lakarea, J. Lianga, and S. Periaswamya. "CAD for Colonography: A tool to address a growing need."

[30] Jerebko, Anna K., James D. Malley, Marek Franaszek, and Ronald M. Summers. "Multiple neural network classification scheme for detection of colonic polyps in CT colonography data sets." Academic Radiology 10, no. 2 (2003): 154-160.

[31] Näppi, Janne, Abraham H. Dachman, Peter MacEneaney, and Hiroyuki Yoshida. "Automated knowledge-guided segmentation of colonic walls for computerized detection of polyps in CT colonography." Journal of computer assisted tomography 26, no. 4 (2002): 493-504.

[32] Acar, Burak, Christopher F. Beaulieu, S. B. Gokturk, Carlo Tomasi, David S. Paik, B. Jeffrey, Judy Yee, and Sandy Napel. "Edge displacement field-based classification for improved detection of polyps in CT colonography." IEEE Transactions on Medical Imaging 21, no. 12 (2002): 1461-1467.

[33] Mohammad Havaei, Axel Davy, David Warde-Farley, Antoine Biard, Aaron Courville, Yoshua Bengio, Chris Pal, Pierre-Marc Jodoin, and Hugo Larochelle. "Brain tumor segmentation with deep neural networks." Medical Image Analysis (2016).

[34] Vibhu Agarwal, and Clayton Carson. "Using Deep Convolutional Neural Networks to Predict Semantic Features of Lesions in Mammograms." (2015).

[35] Fausto Milletari, Nassir Navab, and Seyed-Ahmad Ahmadi. "V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation."arXiv preprint arXiv:1606.04797 (2016).