International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

Computer-Aided Diagnosis for Capsule Endoscopy: From Inception to Future

Kuntesh K. Jani , Subodh Srivastava, Rajeev Srivastava

***Abstract*: *Background:* Gastrointestinal (GI) tract abnormalities are most common across the world, and it is a significant threat to the health of human beings. Capsule endoscopy is a non-sedative, non-invasive and patient-friendly procedure for the diagnosis of GI tract abnormalities. However, it is very time consuming and tiresome task for physicians due to length of endoscopy videos. Thus computer-aided diagnosis (CAD) system is a must.**

***Methods:* This systematic review aims to investigate state-of-the-art CAD systems for automatic abnormality detection in capsule endoscopy by examining publications from scientific databases namely IEEE Xplore, Science Direct, Springer, and Scopus.**

***Results:* Based on defined search criteria and applied inclusion and exclusion criteria, 44 articles are included out of 187. This study presents the current status and analysis of CAD systems for capsule endoscopy.**

***Conclusion:* Publicly available larger dataset and a deep learning based CAD system may help to improve the efficiency of automated abnormality detection in capsule endoscopy.**

***Keywords* : capsule endoscopy, automated abnormality detection, computer-aided diagnosis**

I. INTRODUCTION

Diseases related to Gastrointestinal (GI) tract such as ulcer, bleeding, cancer, Chron's disease and, many more are a significant threat to the health of human beings. GI cancer is not only one of the most common cancers but also one of the most common causes of cancer mortality[1]. As per world health organization (WHO) agency Globocan data 2012, out of estimated 1.01 million new cancer cases in India, 22.7% of cancers were located in GI tract. Similarly, out of about 682,000 cancer-related deaths, approximately 26.6 % deaths were because of GI cancers [2]. The remaining GI tract diseases will certainly add up to the statistics thereby realizing the acute need of precise diagnosis and proper treatment of the same. GI tract diseases are diagnosed mainly by endoscopic procedures namely push endoscopy, enteroscopy, intra-operative endoscopy and capsule endoscopy [3]. Amongst all endoscopic procedures, capsule endoscopy (CE) is an invasion free, sedation free and most friendly procedure for the patients in general and children in particular. Unlike other procedures, cleaning and sterilization is also not a concern as there is no need to retrieve the capsule. Figure 1 shows various components of a swallow-able capsule used for CE.

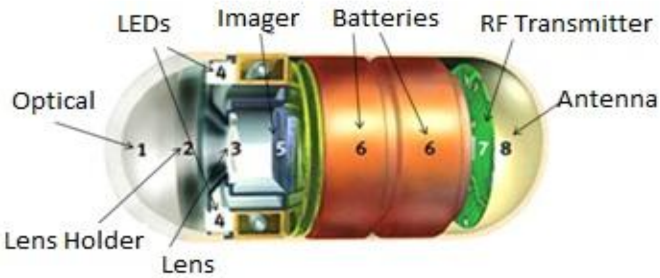

Figure 1: Components Of Swallow-Able Capsule

Given Imaging Inc. introduced CE in the year 2000. The same was approved by the U.S. FDA [4]. Since then over 1,000,000 Pillcam small bowel (SB) capsules have been utilized by year 2015. However, the CE video is very lengthy in nature. The duration the CE video is nearly 8 hours. Such a video generates approximately 60000 images due to which the analysis becomes tiresome and requires lots of time. The large number of images, appearance and dynamics of the GI tract and requirement of focused effort are the reasons affecting the diagnostic procedure. Such a scenario calls for use of a computer-aided diagnosis (CAD) system. Such a system can certainly reduce the effort of experts an hep them with the diagnosis [5]. A CAD can provide a secondary opinion to a gastroenterologist with in a quick and precise system [6]. In the field of imaging in medical science, CAD is an upcoming important research area equipped of providing accurate diagnosis [7]. The final objective of a CAD system is to reduce error in interpretation, reduce search errors and, reduce variation among observers [8]. A typical CAD system for CE may be built from following components: (a) The capsule to capture and transmit data (b) A belt on waist of the patient to receiver and store data (c) A pre-processing and feature extraction component (d) A decision support system built from pattern recognition and machine learning techniques (e) A user interface to generate reports.

The input as received from the capsule contains much of non-informative and noisy content much like any other data acquisition unit. The pre-processing stage insures that such non-informative and noisy components are removed before processing the data to improves upon the computational efficiency and overall system performance [9,10]. The pre-processing and feature extraction converts the input into machine friendly form for improving results [11].

Manuscript published on November 30, 2019.
***** Correspondence Author

Kuntesh K. Jani*, Computer Science and Engineering Department, Indian Institute of Technology (Banaras Hindu University) Varanasi, Uttar Pradesh - 221005, India.

Subodh Srivastava, Electronics and Communication Engineering Department, National Institute of Technology Patna, India.

Rajeev Srivastava Computer Science and Engineering Department, Indian Institute of Technology (Banaras Hindu University) Varanasi.

Some prominent techniques for pre-processing in CE are Poisson maximum likelihood estimation, contrast stretching, histogram equalization and, adaptive contrast diffusion [12,13].

RoI only. It is done by edge based or region based or a combination of both these methods. Few prominent methods for segmentation of CE images are total variation(TV) model – a hybrid active contour model [14], Hidden Markov Model(HMM) - a statistical model [15] and, probabilistic latent semantic analysis(pLSA) - an unsupervised machine learning technique [16].

Feature extraction gives most discriminative and non-redundant information about the image. This is the most critical and the most difficult step [17].

Classification is the final stage of a CAD system. With the aim to discover hidden patterns from the dataset, data mining process assigns classes or labels to different groups using appropriate techniques of machine learning [18,19]. Figure 2 presents the entire process. Core contribution of this study is to present state of the art proposed in the literature on CE abnormality detection that focuses on various features, machine learning techniques and their performance in predicting various abnormalities related to GI tract. The organization of this paper is as follows: Section 2 “Materials and Methods” describes the methodology of conducting this review. Section 3 shows “Results.” Section 4 provides “Discussion” and finally Section 5 gives “Conclusion and future work.”

II. MATERIALS AND METHODS

The objective of this study is to find publications related to CAD systems devised for abnormality detection in CE based on medical image analysis. The primary aim of this review is to provide solutions of following research questions (RQ):

RQ1: What features are currently used for various abnormality related to GI tract as seen through CE?

Segmentation is essentially the process of identifying a region of interest (RoI) from the whole image. So that one can focus on

RQ2: Which techniques are currently devised for CE CAD systems?

RQ3: Which abnormalities are currently addressed?

RQ4: What are the prevailing evaluation criteria for performance assessment of CE CAD system?

RQ5: Which datasets are used for development of CE CAD systems?With the search criteria as “wireless capsule endoscopy,” “engineering,” “computer science,” and “journals” following electronic repositories were searched: IEEE Xplore (www.ieeexplore.ieee .org), Springer (www.link.springer .com), Science Direct (www.sciencedirect.com) and, Scopus (www.scopus.com). Most of the publications are studied till April 2018 since the inception. Few relevant publications may have been left out unintentionally. All relevant publications were studied, but only publications that satisfy the inclusion criteria were included rest were excluded. The inclusion criteria are as follows: (1) at least one GI tract abnormality detection is possible; (2) at least one computer vision or machine learning technique is used; (3) all articles must be full-length papers. This study presents information extracted and analyzed from each paper based on features, techniques used, abnormality addressed, performance and data set used. Figure 3 shows the flow diagram of selection of retrieved studies. It is important to note that many articles used multiple techniques and thus all techniques were counted while summarizing details. Table 1 shows the list of journals and their corresponding number of articles included in this systematic review. 22 articles are from Elsevier journals, 10 articles from IEEE journals, 10 articles from Springer journals and 1 article from PubMed and MDPI. Figure 4 shows year wise number of articles published in various journals stated in Table 1.

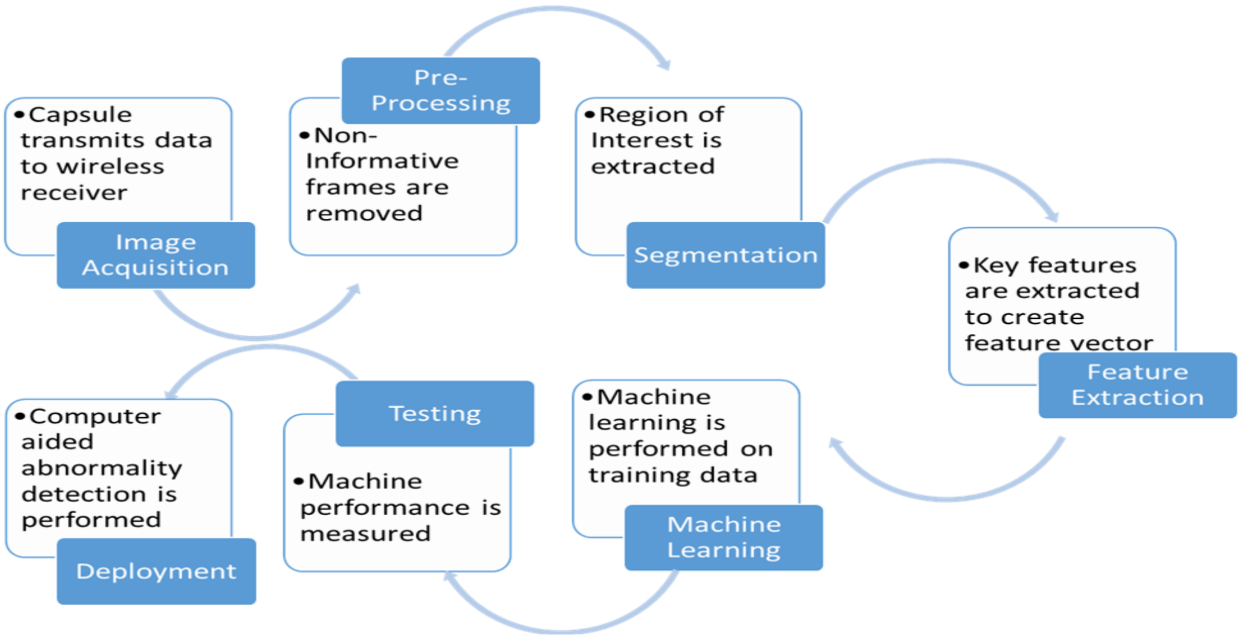

Figure 2: Diagrammatic Representation Of Entire Process

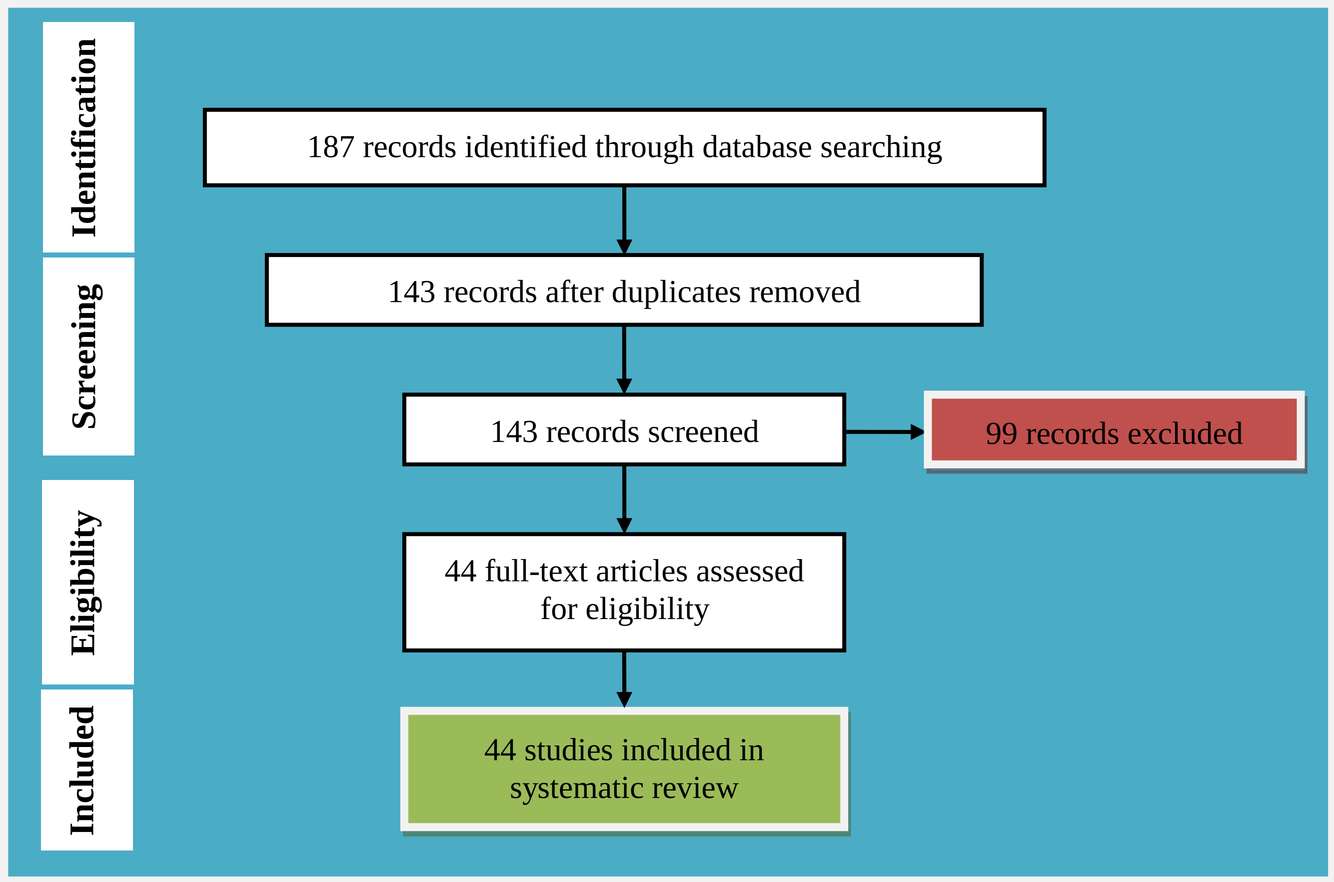

Figure 3: Flow Diagram of selection of retrieved studies

TABLE 1: List Of Journals And Their Corresponding Number Of Articles

Elsevier	Springer	IEEE	MDPI	PubMed
Engineering applications of artificial intelligence (1)	Optimization and engineering (1)	IEEE transactions on biomedical engineering (3)	Applied sciences (1)	Medical electronics & biological engineering (1)
Neurocomputing (2)	Journal of medical systems **(3)**	IEEE transactions on medical imaging (4)		
Biomedical signal processing and control (2)	Medical & biological engineering & computing (1)	IEEE transactions on information technology in biomedicine (1)		
Computers in biology and medicine (7)	Journal of real-time image processing (1)	IEEE journal of biomedical and health informatics (1)		
Image and vision computing (1)	*Journal of shanghai jiaotong university (science) (1)*	IEEE transactions on automation science and engineering (1)		
Artificial intelligence in medicine (1)	Cluster computing (1)			
Computer methods and programs in biomedicine (3)	Multimedia tools and applications (1)			
Expert systems with applications (1)	Ipsj transactions on computer Vision and applications (1)			
Computerized medical imaging and graphics (3)				
Medical image analysis (1)				

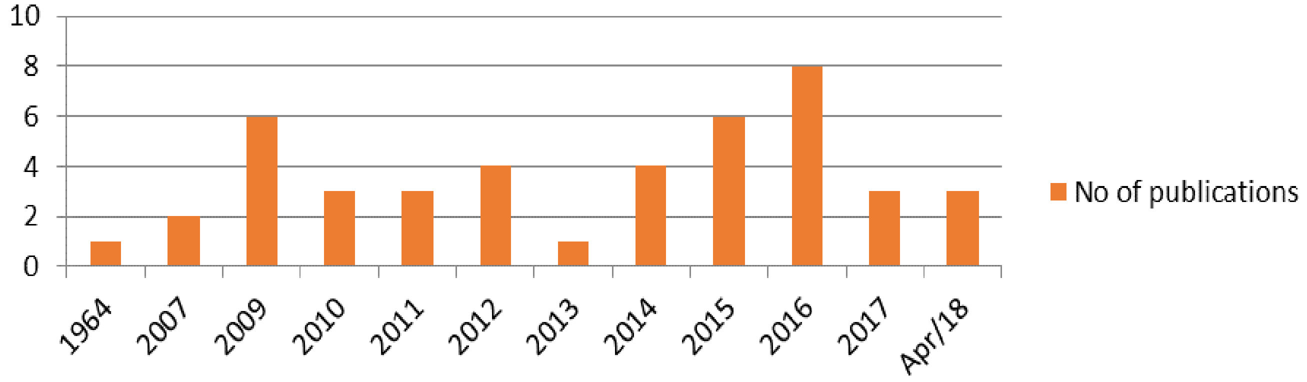

Figure 4: Year-Wise Number Of Papers Included In The Study

III. RESULTS

This study reviewed literature focused on CAD systems for automated abnormality detection in CE. However, CAD system encompasses other components related to computer vision and machine learning which improves or facilitates CAD systems. Image interpretation and image enhancements techniques such as the model of deformable rings (MDR) [20], 3D reconstruction [3] of GI tract and adaptive contrast diffusion [13] provides user-friendly visualization and removes noise related CE images leading to better CAD systems. Redundant image elimination and video summarization techniques such as ensemble classifiers [21], unsupervised data reduction algorithm [22], support vector machine (SVM) based segregation [9], statistical control charts [23], duplicate neighbour removal [10], saliency map [24], Semi-supervised clustering and local scale learning (SS-LSL) [25] reduces the length of the video to be examined thereby saves time and effort. Region identification and segmentation techniques such as super pixel method [26] and Octree-based convolutional neural networks (O-CNN) [27] identify the region of interest. Video and image compression techniques such as JPEG [28], wavelet transform [29], statistic prediction scheme [30], hardware-based approach [31], Differential pulse code modulation (DPCM) [32,33], colour spaced based approaches [34–36], video code based approach [37] compresses the data to make it transfer and storage friendly. In this study, our interest was to explore various computer vision and machine learning technique used in existing CAD systems for abnormality detection in CE. This section presents an analysis of results from 1964 to April 2018. Even though the publication of 1964 did not involve CAD, but it conceptualizes the idea of a radio-pill (wireless capsule) for motility analysis of small bowel. Publications on CAD systems started just a decade back from 2007. The year 2016 has the most number of publications and a new trend towards deep learning for CE is also observed from the same year. Table 2 presents the resultant information divided into features, technique used, abnormality addressed, performance and dataset. Based on data extraction process, the relevant details are summarized in Table 2, and detailed analysis is presented in subsequently.

Table 2: Summary Of Results

Reference	Features	Technique used	Abnormality	Performance	Dataset
[38]	Small intensity movements	-	Motility Analysis	-	-
[39]	Total features: 9*6 = 54. 9 measures for 6 colour planes. { entropy, energy, inverse difference moment, standard deviation, variance, skew, kurtosis, contrast, covariance } *{R, G, B, H, S, V}	Multiple classifier Radial basis function (RBF) and Adaptive neuro-fuzzy logic system (AFLS)	Abnormal image	For RBF Predictability = 95.71% Sensitivity = 95.71% Specificity = 95.71% For AFLS Predictability = 98.57% Sensitivity = 97.18% Specificity = 98.55%	140 images

[11]	Total features: 9*6 = 54. 9 measures for 6 color planes. { entropy, energy, inverse difference moment, standard deviation, variance, skew, kurtosis, contrast, covariance } *{R, G, B, H, S, V}	Multiple classifier RBF+AFLS+ fuzzy inference neural network (FINN)	Abnormal image	For RBF Predictability = 95.71% Sensitivity = 95.71% Specificity = 95.71% Accuracy=91.43% For AFLS Predictability = 98.57% Sensitivity = 97.18% Specificity = 98.55% Accuracy=95.71 For FINN: Accuracy = 94.28%	140 images
[40]	Spatial ,edge and temporal features	Clustering	Motility Analysis	False alarm rate= 37% Detection rate=81%	6 videos
[41]	Total features: 4*3*6 = 72. 4 measures {entropy, intensity, homogeneity, energy} For 3 Discrete wavelet transform (DWT) Components, For 6 colour bands {R,G,B,H,S,V}.	1D classifier with the leave one out method	Abnormal image	Accuracy = 94.7%	75 images
[42]	36 patches on 30 * 30 were identified and chromatic moment for each patch is a feature.	Neural Network (NN)	Ulcer, Bleeding	For Ulcer detection: Specificity=84.68±1.80 Sensitivity=92.97±1.05 For bleeding detection: Specificity=87.81±1.36 Sensitivity=88.62±0.44	100 images
[43]	6 measures {standard deviation, kurtosis, entropy, energy, skew, mean} of uniform LBP histogram.	Multi layer Perceptron (MLP), SVM	Ulcer	Accuracy=92.37%, Sensitivity=93.28% Specificity=91.46%,	100 images
[44]	Total features: 256*3 = 768 Pixel intensity value of image block size 256 for each of color plane {R, G, B}.	SVM	Bleeding	Accuracy = 99%	640 images
[45]	6 measures {standard deviation, kurtosis, entropy, energy, skew, mean} of LBP histogram from I color space of HSI and Chromatic moments	MLP	Bleeding	Detection rate = 90%	200 images
[46]	GI myoelectrical activity	Fast Fourier transform (FFT)	Motility Analysis	-	2 videos
[47]	Blob, color and texture based 54 features	SVM	Motility Analysis	Sensitivity=70%	10 videos
[48]	Pixel intensity and distance map	Clustering	Bleeding	Sensitivity = 92%, Specificity = 95%	960 images
[49]	Geometric features {entropy, contrast, homogeneity, inverse moment}	SVM	Ulcer, Polyp	For ulcer detection: Sensitivity=75% Specificity=73.3% For polyp detection: Sensitivity=96.75% Specificity=72.45%	50 images

[50]	Total features: 3*3*6=54. 3 bands {LH,HL,HH} * 3 colour planes {R,G,B} * 6 statistical measures {standard deviation, skew, energy, mean, kurtosis, entropy }	Ensemble classifier	Tumor	Accuracy=90.50%, Sensitivity=92.33% Specificity=88.67%.	1200 images
[51]	colour features values of {R,G,B,H,S,I} Total features: 6	Probabilistic neural network (PNN)	Bleeding	Sensitivity=93.1% Specificity=85.5%.	14630 images
[52]	Dif lac analysis represents the feature vector.	Linear classifier, Mahalanobis, SVM-RBF, NN	Abnormal image	Mean accuracy > 95%	176 images
[53]	18 Uniform LBP features	SVM	Polyp	Accuracy=91.6% for RGB colour space	1200 images
[54]	6 measures (standard deviation, skew, kurtosis, entropy, energy, mean) of Texture spectrum histogram (TSH), RIULBP and Curvelet-based local binary pattern (CLBP) and Colour wavelet covariance (CWC) is taken as a feature vector	SVM	Tumor	For RIULBP color features Average accuracy = 83.50%	1200 images
[55]	Uniform LBP histogram {10}, 2 level DWT {7}, 3 bands for 3 colour space =10*7*3*3=630 features.	SVM	Tumor	Detection Accuracy = 92.4%	1200 images
[56]	-	Dynamic programming	Motility Analysis	Visual inspection is 4 times faster	videos
[57]	279 texture features And 21 color bands lead to 279*21=5859 features. Reduced to 2494 features	Vector supported convex hull method	Bleeding, Ulcer	For bleeding: Recall = 0.875 Precision =0.732 Jaccard index =0.487 For Focal Ulcer: Recall = 0.932 Precision =0.696 Jaccard index= 0.235 For Excessive Ulcer: Recall=0.917 Precision =0.669 Jaccard index= 0.621	613 images
[58]	5 measures { entropy, energy, mean, standard deviation, skew} from 3 colour space {R,G,B} Total features: 15	MLP	Bleeding	Specificity=90%, Sensitivity=96%, Accuracy=93%	100 images
[59]	130 texton histograms generated from Leung and Malik (LM) and LBP filter	k-nearest neighbour (KNN)	Bleeding, Erythema, Erosion, Ulcer, Polyp	Recall =92% and Specificity =91.8%	1750 images
[60]	Geometric feature	Binary classifier	Polyp	Sensitivity=81% Specificity =90%	18968 images
[4]	Total features: 24+80+14= 118 24 color, 80 edge, and 14 texture features.	SVM-RBF, HMM	Polyp	For Polyp: Accuracy=0.933 Recall =0.933	13 videos

[61]	Total Features: 6*3=18 Normalized GLCM and Haralick based 6 features{contrast, sum entropy, sum variance, difference variance, difference average, Entropy} for 3 colour bands {R,G,B}	SVM	Bleeding	Accuracy=99.19%, Sensitivity99.41%= and Specificity=98.95%	2920 images
[62]	Color features	Binary classifier	Bleeding	Processing rate: 344 fps which is 256 times faster than sequential execution	-
[63]	Total features: 85+24+12=121 MPEG-7 edge features, texture and color features.	SVM	Crohn's Disease	Precision and Recall > 90%	513 images
[64]	The saliency of color and texture	SVM	Ulcer	Accuracy=92.65% Sensitivity=94.12%	340 images
[65]	Motility bar	Mean shift clustering	Motility analysis	-	10 videos
[66]	Edge density estimation	The parallel executable algorithm	Inflammation	Basic approach: Accuracy=84% Advanced approach: Accuracy=90%	231 images
[67]	Total features: 310 6 texture descriptors will result in 126-second order statistics and 84 high order moments.	Genetic Algorithm (GA), SVM	Tumor	Accuracy=97.3%, Sensitivity=97.8%, Specificity=96.7%	1800 images
[68]	H,S,V colour space pixel intensity values	SVM	Bleeding	Sensitivity 94% , Specificity 91%, Accuracy 92%	8500 images
[69]	YCbCr and Joint diagonalization principal component analysis (JD-PCA) based features	ODR-BSMOTE-SVM (OB-SVM)	Cancer	Oesophageal cancer images: Accuracy=90.75%, Standard deviations=0.0426 Areas under the curves=0.9471 Standard deviations=0.0296 Early gastric cancer images: Accuracy=90.75% Standard deviations=0.0334 Areas under the curves=0.9532 Standard deviations=0.0285 Small intestinal	1330 images

				bleeding images: Accuracy=94.34%, Standard deviations= 0.0235 Areas under the curves=0.9776 Standard deviations=0.0172	
[70]	Colour features	SVM	Bleeding	Accuracy= 95.75%, Sensitivity= 92% , Specificity= 96.5%, AUC = 0.9771	2400 images
[71]	SIFT+CLBP based 384 features	SVM	Polyp	Accuracy=93.20%	2500 images
[72]	Histogram of avg. intensity	Rusboost	Hookworm	Accuracy=78.2%, Sensitivity=77.2%, Specificity=77.9%	44000 0 images
[73]	Generic features	Convolutional neural networks (CNN)	Motility Analysis	Mean accuracy=96%	12000 0 images
[74]	Cluster based features	k-mean clusturing, SVM	Bleeding	sensitivity =96.22%, specificity=98.54% , accuracy = 98.04%	2350 images
[75]	Total features: 5*3 planes =15. Mean, Standard deviation, Entropy, Skew and Energy	SVM	Bleeding	accuracy = 95%, sensitivity = 94% ,specificity = 95.3%	8872 images
[76]	Centroid, area, eccentricity, mean, standard deviation	Naïve Bayes	Bleeding	-	-
[77]	Total features: 54 (9 LBPV histograms of 9 DWT components * 6 statistical features)	SVM, MLP	Abnormal images	Accuracy =97.0 %, Sensitivity =96.4 %, Specificity =98.5 %	1670 images
[78]	Statistical features	SVM	Ulcer	Accuracy =97.89%, Sensitivity =96.22%, Specificity =95.09%	48000 images
[79]	Kanade-Lucas-Tomasi (KLT) feature points	Affine transform	Red spot, Phlebectasi, Angiodysplasia, Lymphangiectasia, Erosion, Erythematous, Ulcer, and White-tipped villi	-	120 images

A. Features used

The features must be optimal in size and should be able to distinguish between normal and abnormal images. Since different abnormalities exhibit different properties, a wide range of features is used as observed in this study. Figure 5 shows image of a few abnormalities [80]. Textural, color, geometric, spatial, edge, temporal and generic features are amongst the most used features. Novel hybrid features like curvlet based LBP, distance map and texton number are also experimented in a few publications.

a b c

Figure 5: Images Of Various Abnormalities (A) Bleeding (B) Ulcer (C) Angioectasia

General prediction about presence or absence of abnormality uses features such as textural, combination of statistical measures with DWT transform bands and Dif Lac analysis.

Ulcer detection uses features such as chromatic moments, textural, geometric, a combination of statistical measures over different color planes and the combination of color and texture features.

Motility analysis uses features such as cluster-based, spatial, edge, temporal, a combination of color and textural and generic ones.

Bleeding detection uses features such as a combination of statistical measures over different color space, cluster-based, color and textural features.

The extracted features are fed to a classifier for CAD of CE images.

B. Machine learning techniques used

Several machine learning techniques are used in CAD systems for detection, classification, and diagnosis of abnormalities of GI tract. Essentially the input data called training data is used to generate a model for classification. Then this model is tested on another set of input data called testing data. If the performance is not satisfactory, then the model can be re-trained with different parameters to achieve acceptable performance. Based on features extracted the machine learning model is established and employed to detect GI tract abnormalities from CE images automatically. The obtained data is analyzed using a pie chart as shown in figure 6. SVM is a supervised classifier, and it is found to be the most used machine learning technique in the publications studied in this systematic review. Based on training data SVM creates a hyperplane which is used as a boundary to differentiate between two classes of data. The closest points to the hyperplane play a significant role as they define the class margins or boundaries[81]. Once this model is created, it is used to classify unknown instances of testing data. In this systematic review, 41% of all techniques use SVM. Clustering is unsupervised machine learning technique. It works on the concept of similarity measures. Instances with most similarity are grouped, and similarity between two groups is very less. Based on pixel intensity and distance map regions with and without bleeding are efficiently identified in [48]. Clustering techniques are also used for segmentation and feature extraction in the studied literature. Neural network classifier is inspired from a biological neuron. It is made up of consecutive layers namely input layer, a hidden layer, and an output layer. Articles examined in this study use the fuzzy neural network, probabilistic neural network and multilayer perceptron for abnormality detection. Ensemble classifier encompasses optimized classifiers, and the final output is obtained using combination rules such as voting. It is observed from this study that stand alone classifiers outperform ensemble systems.

C. Evaluation metrics

It is important to access the performance of the techniques employed for CAD systems especially in sensitive fields such as medical diagnosis. This study shows that there are several ways for the same. The most used performance evaluators are accuracy, sensitivity, and specificity. The area under the curve (AUC), Jaccard index and standard deviation are amongst other performance evaluators. Most used metrics are defined as follows: (1) Accuracy is the percentage of correctly classified samples from total samples. (2) Sensitivity is a percentage of abnormal samples correctly classified. (3) Specificity is a percentage of normal samples correctly classified.

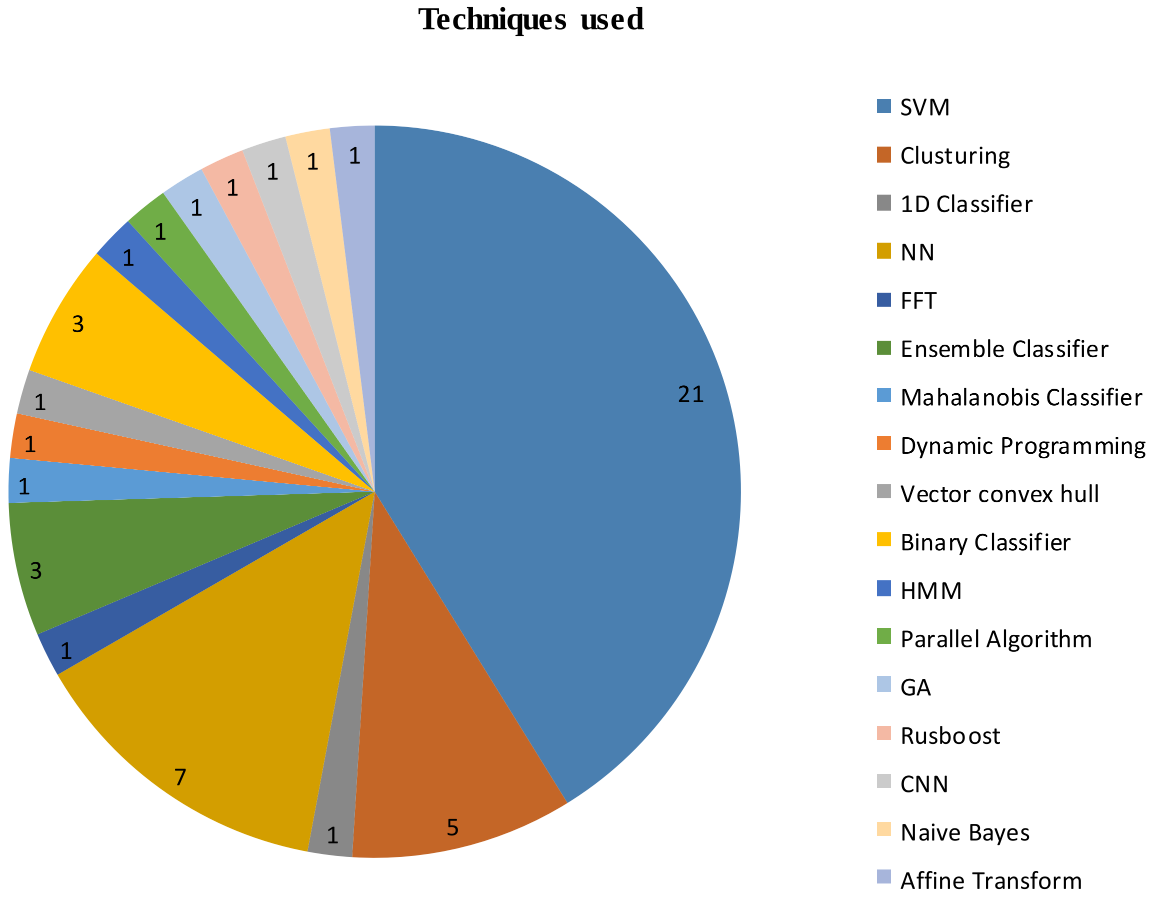

Figure 6: Pie Chart Of Various Techniques Used In Cad Systems For Ce Abnormality Detection

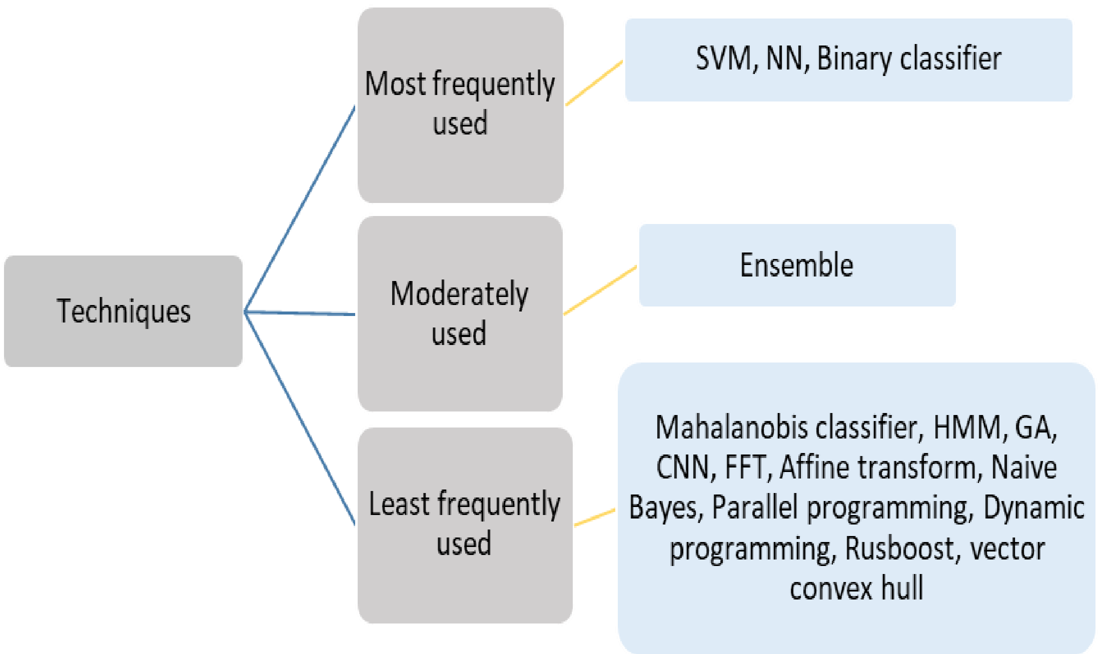

Figure 7: Categorization Of Techniques

IV. DISCUSSION

This study observes that optimized feature set capable of differencing between multiple abnormalities is yet to be designed. Further, analysis of computation time and space required is necessary for designing the most appropriate feature set. Other features such as geometric, kinetics and binary object features can be explored. It is also observed that machine learning techniques are widely used in CAD systems for GI tract abnormality detection in CE images. However, there is wide variation in frequency of each technique used. Figure 7 presents frequency based categorization of techniques used in CAD systems.

SVM and artificial neural network are found to be most used classifier in CAD systems. Different hybrid variants of both these classifiers are found widely experimented throughout the examined papers of this systematic review. From the various dataset used in different studies under this systematic review, it is learned that most of the times skewed data is fed into machine learning techniques. This unbalanced data problem can be better evaluated by Matthew's Correlation Coefficient (MCC). MCC is very useful in case of skewed data between classes [82]. To provide an exact idea about the current scenario of CAD systems for CE abnormality detection, table 3 shows maximum accuracy achieved to detect various GI tract abnormalities along with the technique used to detect it.

Table 3: Techniques Used To Detect Various Abnormalities With Maximum Achieved Accuracy

Abnormality	Max. Accuracy in %	Technique(s)
Abnormal images	97.0	SVM, MLP
Motility analysis	96.0	CNN
Ulcer	97.89	SVM
Bleeding	99.19	SVM
Polyp	93.3	SVM-RBF, HMM
Tumor	97.3	SVM, GA
Cancer	90.75	OB-SVM
Inflammation	90	Parallel Algorithm
Hookworm	78.2	Rusboost

Despite the promising results shown in Table 3, following disadvantages are noted in general from different articles studied in this review:

- Size of the dataset is small
- Only a specific set of features are explored ignoring other relevant ones
- Overfitting due to use of local features
- Skewed data
- Computationally expensive techniques
- Clinical validation of CAD system is not done

V. CONCLUSION AND FUTURE WORK

The aim of this systematic review is to help researchers design and develop CAD systems for detecting GI tract abnormalities through CE procedure. Such CAD systems will prove fruitful in timely detection and treatment of GI tract abnormalities. The state-of-the-art of computer vision and machine learning techniques has been explored in this study. It is found that comprehensive comparison of various methods is very difficult due to several factors such as different dataset, varying size of the dataset, different approaches adopted for assessment, wide range of feature sets and different methods of parameter tuning.

As future work, it is recommended to have gold standard dataset available in public domain so that researches and experts can contribute from all different perspectives to improve CAD systems. Moreover, a highly promising trend of deep learning has surfaced in recent years. Developing a deep learning based CAD system may help to improve the efficiency of automated abnormality detection.

REFERENCES

1. Sharma A-ND. Gastrointestinal cancers in India: Treatment perspective Review Article. South Asian J Cancer 2016;5(3):125–6. https://doi.org/10.4103/2278-330X.187580.
2. WHO GLOBOCAN 2012. http://globocan.iarc.fr/Pages/summary_table_pop_sel.aspx (accessed March 31, 2018).
3. Karargyris A, Bourbakis N. Three-dimensional reconstruction of the digestive wall in capsule endoscopy videos using elastic video interpolation. IEEE Trans Med Imaging 2011;30:957–71. https://doi.org/10.1109/TMI.2010.2098882.
4. Zhao Q, Mullin GE, Meng MQH, Dassopoulos T, Kumar R. A general framework for wireless capsule endoscopy study synopsis. Comput Med Imaging Graph 2015;41:108–16. https://doi.org/10.1016/j.compmedimag.2014.05.011.
5. Yassin NIR, Omran S, Houby EMF El, Allam H. Machine Learning Techniques for Breast Cancer Computer Aided Diagnosis Using Different Image Modalities: A Systematic Review. Comput Methods Programs Biomed 2017;156:25–45. https://doi.org/10.1016/j.cmpb.2017.12.012.
6. Riaz F, Hassan A, Nisar R, Dinis-Ribeiro M, Coimbra MT. Content-Adaptive Region-Based Color Texture Descriptors for Medical Images. IEEE J Biomed Heal Informatics 2017;21:162–71. https://doi.org/10.1109/JBHI.2015.2492464.
7. Doi K. Computer-aided diagnosis in medical imaging: Historical review, current status and future potential. Comput Med Imaging Graph 2007;31:198–211. https://doi.org/10.1016/j.compmedimag.2007.02.002.
8. Giger ML, Chan H-P, Boone J. Anniversary Paper: History and status of CAD and quantitative image analysis: The role of *Medical Physics* and AAPM. Med Phys 2008;35:5799–820. https://doi.org/10.1118/1.3013555.
9. Bashar MK, Kitasaka T, Suenaga Y, Mekada Y, Mori K. Automatic detection of informative frames from wireless capsule endoscopy images. Med Image Anal 2010;14:449–70. https://doi.org/10.1016/j.media.2009.12.001.
10. Lee HG, Choi MK, Shin BS, Lee SC. Reducing redundancy in wireless capsule endoscopy videos. Comput Biol Med 2013;43:670–82. https://doi.org/10.1016/j.compbiomed.2013.02.009.
11. Kodogiannis VS, Boulougoura M, Lygouras JN, Petrounias I. A neuro-fuzzy-based system for detecting abnormal patterns in wireless-capsule endoscopic images. Neurocomputing 2007;70:704–17. https://doi.org/10.1016/j.neucom.2006.10.024.
12. Srivastava R, Srivastava S. Restoration of Poisson noise corrupted digital images with nonlinear PDE based filters along with the choice of regularization parameter estimation. Pattern Recognit Lett 2013;34:1175–85. https://doi.org/10.1016/j.patrec.2013.03.026.
13. Li B, Meng MQH. Wireless capsule endoscopy images enhancement via adaptive contrast diffusion. J Vis Commun Image Represent 2012;23:222–8. https://doi.org/10.1016/j.jvcir.2011.10.002.
14. Yihua Lan, Xingang Zhang, Zhidu Liu LZ and ML. Hybrid Segmentation using region information for wireless capsule endoscopy images. Inf Technol J 2013;12:3815–9.
15. Mackiewicz M., Berens J;, Fisher M. Wireless Capsule Endoscopy Color Video Segmentation. IEEE Trans Med Imaging 2008;27:1769–81. https://doi.org/10.1109/TMI.2008.926061.
16. Shen Y, Guturu PP, Buckles BP. Wireless capsule endoscopy video segmentation using an unsupervised learning approach based on probabilistic latent semantic analysis with scale invariant features. IEEE Trans Inf Technol Biomed 2012;16:98–105.

https://doi.org/10.1109/TITB.2011.2171977.
17. Jiang X. Feature extraction for image recognition and computer vision. Proc - 2009 2nd IEEE Int Conf Comput Sci Inf Technol ICCSIT 2009 2009:1–15. https://doi.org/10.1109/ICCSIT.2009.5235014.
18. Jalalian A, Mashohor SBT, Mahmud HR, Saripan MIB, Ramli ARB, Karasfi B. Computer-aided detection/diagnosis of breast cancer in mammography and ultrasound: A review. Clin Imaging 2013;37:420–6. https://doi.org/10.1016/j.clinimag.2012.09.024.
19. Han J, Kamber M. Data Mining: Concepts and Techniques. 2006.
20. Szczypiński PM, Sriram RD, Sriram PVJ, Reddy DN. A model of deformable rings for interpretation of wireless capsule endoscopic videos. Med Image Anal 2009;13:312–24. https://doi.org/10.1016/j.media.2008.12.002.
21. Vilariño F, Kuncheva LI, Radeva P. ROC curves and video analysis optimization in intestinal capsule endoscopy. Pattern Recognit Lett 2006;27:875–81. https://doi.org/10.1016/j.patrec.2005.10.011.
22. Iakovidis DK, Tsevas S, Polydorou A. Reduction of capsule endoscopy reading times by unsupervised image mining. Comput Med Imaging Graph 2010;34:471–8. https://doi.org/10.1016/j.compmedimag.2009.11.005.
23. Li C, Hamza A Ben, Bouguila N, Wang X, Ming F, Xiao G. Online redundant image elimination and its application to wireless capsule endoscopy. Signal, Image Video Process 2012;8:1497–506. https://doi.org/10.1007/s11760-012-0384-3.
24. Mehmood I, Sajjad M, Baik SW. Video summarization based tele-endoscopy: A service to efficiently manage visual data generated during wireless capsule endoscopy procedure. J Med Syst 2014;38. https://doi.org/10.1007/s10916-014-0109-y.
25. Ben Ismail MM, Bchir O. Endoscopy video summarisation using novel relational motion histogram descriptor and semi-supervised clustering. J Exp Theor Artif Intell 2016;28:629–53. https://doi.org/10.1080/0952813X.2015.1020623.
26. Arivazhagan S, Sylvia Lilly Jebarani W, Jenifer Daisy V. Categorization and segmentation of intestinal content and pathological frames in wireless capsule endoscopy images. Int J Imaging Robot 2014;13:134–47. https://doi.org/10.1109/TITB.2012.2221472.
27. Chen H, Wu X, Tao G, Peng Q. Automatic content understanding with cascaded spatial–temporal deep framework for capsule endoscopy videos. Neurocomputing 2017;229:77–87. https://doi.org/10.1016/j.neucom.2016.06.077.
28. Turgis D, Puers R. Image compression in video radio transmission for capsule endoscopy. Sensors Actuators, A Phys 2005;123–124:129–36. https://doi.org/10.1016/j.sna.2005.05.016.
29. Thoné J, Verlinden J, Puers R. An efficient hardware-optimized compression algorithm for wireless capsule endoscopy image transmission. Procedia Eng 2010;5:208–11. https://doi.org/10.1016/j.proeng.2010.09.084.
30. Khan TH, Wahid KA. Lossless and low-power image compressor for wireless capsule endoscopy. VLSI Des 2011;2011. https://doi.org/10.1155/2011/343787.
31. Turcza P, Duplaga M. Low power FPGA-based image processing core for wireless capsule endoscopy. Sensors Actuators, A Phys 2011;172:552–60. https://doi.org/10.1016/j.sna.2011.09.026.
32. Khan T, Wahid K. Low power and low complexity compressor for video capsule endoscopy. Circuits Syst Video … 2011;21:1534–46. https://doi.org/10.1109/TCSVT.2011.2163985.
33. Khan TH, Wahid KA. Subsample-based image compression for capsule endoscopy. J Real-Time Image Process 2013;8:5–19. https://doi.org/10.1007/s11554-011-0208-7.
34. Khan TH, Wahid K. Low-complexity colour-space for capsule endoscopy image compression. Electron Lett 2011;47:1217. https://doi.org/10.1049/el.2011.2211.
35. Khan TH, Wahid KA. White and narrow band image compressor based on a new color space for capsule endoscopy. Signal Process Image Commun 2014;29:345–60. https://doi.org/10.1016/j.image.2013.12.001.
36. Fante KA, Bhaumik B, Chatterjee S. Design and Implementation of Computationally Efficient Image Compressor for Wireless Capsule Endoscopy. Circuits, Syst Signal Process 2016;35:1677–703. https://doi.org/10.1007/s00034-015-0136-z.
37. Deligiannis N, Verbist F, Iossifides AC, Slowack J, Van de Walle R, Schelkens P, et al. Wyner-Ziv video coding for wireless lightweight multimedia applications. EURASIP J Wirel Commun Netw 2012;2012:106. https://doi.org/10.1186/1687-1499-2012-106.
38. B. Ross BWW and AWK. Bibliography and abstracts. Med Electron Biol Engng 1964;2:349–77. https://doi.org/10.1288/00005537-189807000-00013.
39. Kodogiannis VS, Boulougoura M, Wadge E, Lygouras JN. The usage of soft-computing methodologies in interpreting capsule endoscopy. Eng Appl Artif Intell 2007;20:539–53. https://doi.org/10.1016/j.engappai.2006.09.006.
40. Vu H, Echigo T, Sagawa R, Yagi K, Shiba M, Higuchi K, et al. Detection of contractions in adaptive transit time of the small bowel from wireless capsule endoscopy videos. Comput Biol Med 2009;39:16–26. https://doi.org/10.1016/j.compbiomed.2008.10.005.
41. Bonnel J, Khademi A, Krishnan S, Ioana C. Small bowel image classification using cross-co-occurrence matrices on wavelet domain. Biomed Signal Process Control 2009;4:7–15. https://doi.org/10.1016/j.bspc.2008.07.002.
42. Li B, Meng MQH. Computer-based detection of bleeding and ulcer in wireless capsule endoscopy images by chromaticity moments. Comput Biol Med 2009;39:141–7. https://doi.org/10.1016/j.compbiomed.2008.11.007.
43. Li B, Meng MQH. Texture analysis for ulcer detection in capsule endoscopy images. Image Vis Comput 2009;27:1336–42. https://doi.org/10.1016/j.imavis.2008.12.003.
44. Liu J, Yuan X. Obscure bleeding detection in endoscopy images using support vector machines. Optim Eng 2009;10:289–99. https://doi.org/10.1007/s11081-008-9066-y.
45. Li B, Meng MQH. Computer-aided detection of bleeding regions for capsule endoscopy images. IEEE Trans Biomed Eng 2009;56:1032–9. https://doi.org/10.1109/TBME.2008.2010526.
46. Woo SH, Cho JH. Telemetry system for slow wave measurement from the small bowel. MedBiolEng Comput 2010;48:277–83. https://doi.org/10.1007/s11517-009-0567-4.
47. Vilariño F, Spyridonos P, Deiorio F, Vitria J, Azpiroz F, Radeva P. Intestinal motility assessment with video capsule endoscopy: Automatic annotation of phasic intestinal contractions. IEEE Trans Med Imaging 2010;29:246–59. https://doi.org/10.1109/TMI.2009.2020753.
48. Pan GB, Yan GZ, Song XS, Qiu XL. Bleeding detection from wireless capsule endoscopy images using improved euler distance in CIELab. J Shanghai Jiaotong Univ 2010;15:218–23. https://doi.org/10.1007/s12204-010-9716-z.
49. Karargyris A, Bourbakis N. Detection of small bowel polyps and ulcers in wireless capsule endoscopy videos. IEEE Trans Biomed Eng 2011;58:2777–86. https://doi.org/10.1109/TBME.2011.2155064.
50. Li B, Meng MQH, Lau JYW. Computer-aided small bowel tumor detection for capsule endoscopy. Artif Intell Med 2011;52:11–6. https://doi.org/10.1016/j.artmed.2011.01.003.
51. Pan G, Yan G, Qiu X, Cui J. Bleeding detection in wireless capsule Endoscopy based on probabilistic neural network. J Med Syst 2011;35:1477–84. https://doi.org/10.1007/s10916-009-9424-0.
52. Charisis VS, Hadjileontiadis LJ, Liatsos CN, Mavrogiannis CC, Sergiadis GD. Capsule endoscopy image analysis using texture information from various colour models. Comput Methods Programs Biomed 2012;107:61–74. https://doi.org/10.1016/j.cmpb.2011.10.004.
53. Li B, Meng MQ-H. Automatic polyp detection for wireless capsule endoscopy images. Expert Syst Appl 2012;39:10952–8. https://doi.org/10.1016/j.eswa.2012.03.029.
54. Li BP, Meng MQH. Comparison of several texture features for tumor detection in CE images. J Med Syst 2012;36:2463–9. https://doi.org/10.1007/s10916-011-9713-2.
55. Li B, Meng MQH. Tumor recognition in wireless capsule endoscopy images using textural features and SVM-based feature selection. IEEE Trans Inf Technol Biomed 2012;16:323–9. https://doi.org/10.1109/TITB.2012.2185807.
56. Drozdzal M, Segu?? S, Vitri?? J, Malagelada C, Azpiroz F, Radeva P. Adaptable image cuts for motility inspection using WCE. Comput Med Imaging Graph 2013;37:72–80. https://doi.org/10.1016/j.compmedimag.2012.09.002.
57. Szczypiński P, Klepaczko A, Pazurek M, Daniel P. Texture and color based image segmentation and pathology detection in capsule endoscopy videos. Comput Methods Programs Biomed 2014;113:396–411. https://doi.org/10.1016/j.cmpb.2012.09.004.
58. Sainju S, Bui FM, Wahid KA. Automated bleeding detection in capsule endoscopy videos using statistical features and region growing. J Med Syst 2014;38. https://doi.org/10.1007/s10916-014-0025-1.
59. Nawarathna R, Oh JH, Muthukudage J, Tavanapong W, Wong J, de Groen PC, et al. Abnormal image detection in endoscopy videos using a filter bank and local binary patterns. Neurocomputing 2014;144:70–91.

https://doi.org/10.1016/j.neucom.2014.02.064.
60. Mamonov A V, Figueiredo IN, Figueiredo PN, Tsai YR. Automated polyp detection in colon capsule endoscopy by Automated polyp detection in colon capsule endoscopy. Ices Rep 13-10 2013;33:1–16.
61. Hassan AR, Haque MA. Computer-aided gastrointestinal hemorrhage detection in wireless capsule endoscopy videos. Comput Methods Programs Biomed 2015;122:341–53. https://doi.org/10.1016/j.cmpb.2015.09.005.
62. Graca C, Falcao G, Figueiredo IN, Kumar S. Hybrid multi-GPU computing: accelerated kernels for segmentation and object detection with medical image processing applications. J Real-Time Image Process 2017;13:227–44. https://doi.org/10.1007/s11554-015-0517-3.
63. Kumar R, Zhao Q, Seshamani S, Mullin G, Hager G, Dassopoulos T. Assessment of crohn’s disease lesions in wireless capsule endoscopy images. IEEE Trans Biomed Eng 2012;59:355–62. https://doi.org/10.1109/TBME.2011.2172438.
64. Yuan Y, Wang J, Li B, Meng M q-HH. Saliency Based Ulcer Detection for Wireless Capsule Endoscopy Diagnosis. IEEE Trans Med Imaging 2015;34:2046–57. https://doi.org/10.1109/TMI.2015.2418534.
65. Drozdzal M, Seguí S, Radeva P, Malagelada C, Azpiroz F, Vitrià J. Motility bar: A new tool for motility analysis of endoluminal videos. Comput Biol Med 2015;65:320–30. https://doi.org/10.1016/j.compbiomed.2015.04.006.
66. Ševo I, Avramović A, Balasingham I, Elle OJ, Bergsland J, Aabakken L. Edge density based automatic detection of inflammation in colonoscopy videos. Comput Biol Med 2016;72:138–50. https://doi.org/10.1016/j.compbiomed.2016.03.017.
67. Liu G, Yan G, Kuang S, Wang Y. Detection of small bowel tumor based on multi-scale curvelet analysis and fractal technology in capsule endoscopy. Comput Biol Med 2016;70:131–8. https://doi.org/10.1016/j.compbiomed.2016.01.021.
68. Usman MA, Satrya GB, Usman MR, Shin SY. Detection of small colon bleeding in wireless capsule endoscopy videos. Comput Med Imaging Graph 2016;54:16–26. https://doi.org/10.1016/j.compmedimag.2016.09.005.
69. Liu DY, Gan T, Rao NN, Xing YW, Zheng J, Li S, et al. Identification of lesion images from gastrointestinal endoscope based on feature extraction of combinational methods with and without learning process. Med Image Anal 2016;32:281–94. https://doi.org/10.1016/j.media.2016.04.007.
70. Yuan Y, Li B, Meng MQH. Bleeding Frame and Region Detection in the Wireless Capsule Endoscopy Video. IEEE J Biomed Heal Informatics 2016;20:624–30. https://doi.org/10.1109/JBHI.2015.2399502.
71. Yuan Y, Li B, Meng MQH. Improved Bag of Feature for Automatic Polyp Detection in Wireless Capsule Endoscopy Images. IEEE Trans Autom Sci Eng 2016;13:529–35. https://doi.org/10.1109/TASE.2015.2395429.
72. Wu X, Chen H, Gan T, Chen J, Ngo CW, Peng Q. Automatic Hookworm Detection in Wireless Capsule Endoscopy Images. IEEE Trans Med Imaging 2016;35:1741–52. https://doi.org/10.1109/TMI.2016.2527736.
73. Seguí S, Drozdzal M, Pascual G, Radeva P, Malagelada C, Azpiroz F, et al. Generic feature learning for wireless capsule endoscopy analysis. Comput Biol Med 2016;79:163–72. https://doi.org/10.1016/j.compbiomed.2016.10.011.
74. Ghosh T, Fattah SA, Wahid KA, Zhu WP, Ahmad MO. Cluster based statistical feature extraction method for automatic bleeding detection in wireless capsule endoscopy video. Comput Biol Med 2018;94:41–54. https://doi.org/10.1016/j.compbiomed.2017.12.014.
75. Deeba F, Islam M, Bui FM, Wahid KA. Performance assessment of a bleeding detection algorithm for endoscopic video based on classifier fusion method and exhaustive feature selection. Biomed Signal Process Control 2018;40:415–24. https://doi.org/10.1016/j.bspc.2017.10.011.
76. Sivakumar P, Kumar BM. A novel method to detect bleeding frame and region in wireless capsule endoscopy video. Cluster Comput 2018:1–7. https://doi.org/10.1007/s10586-017-1584-y.
77. Charfi S, Ansari M El. Computer-aided diagnosis system for colon abnormalities detection in wireless capsule endoscopy images. Multimed Tools Appl 2018;77:4047–64. https://doi.org/10.1007/s11042-017-4555-7.
78. Suman S, Hussin FA, Malik AS, Ho SH, Hilmi I, Leow AH-R, et al. Feature selection and classification of ulcerated lesions using statistical analysis for WCE images. Appl Sci 2017;7. https://doi.org/10.3390/app7101097.
79. Yanagawa Y, Echigo T, Vu H, Okazaki H, Fujiwara Y, Arakawa T, et al. Abnormality tracking during video capsule endoscopy using an affine triangular constraint based on surrounding features. IPSJ Trans Comput Vis Appl 2017;9:1–10. https://doi.org/10.1186/s41074-017-0015-6.
80. Spyrou E, Iakovidis DK. Video-based measurements for wireless capsule endoscope tracking. Meas Sci Technol 2014;25. https://doi.org/10.1088/0957-0233/25/1/015002.
81. Subasi A. Classification of EMG signals using PSO optimized SVM for diagnosis of neuromuscular disorders. Comput Biol Med 2013;43:576–86. https://doi.org/10.1016/j.compbiomed.2013.01.020.
82. Singh VP, Srivastava R. Improved image retrieval using fast Colour-texture features with varying weighted similarity measure and random forests. Multimed Tools Appl 2017:1–26. https://doi.org/10.1007/s11042-017-5036-8.

AUTHORS PROFILE

Kuntesh K Jani is currently a PhD research scholar in Computer Science and Engineering at the Indian Institute of Technology (BHU), Varanasi, India.

Subodh Srivastava is working as assistant professor in the Electronics and Communication Engineering Department at National Institute of Technology, Patna, India. He has having 30+ publication in reputed journals and conferences.

Rajeev Srivastava is working as a Professor in the Department of Computer Science and Engineering at Indian Institute of Technology (Banaras Hindu University), Varanasi, India. He has nearly 20 years of teaching and research experience. He has more than 100 research publications to his credit.