A Review on Computational Approaches for Disease Diagnosis in Wireless Capsule Endoscopy Images

Mrs.R.Sathiya, [*1], Dr.R.Kalaimagal,[**2]
*Research Scholar in Bharathiyar University, Coimbatore, India.
**Associate Professor of Computer Science, Government Arts college for Men(Autonomous), Nandhanam, Chennai, India.

Abstract: *Wireless Capsule Endoscopy (WCE) is a commonly used technique for the examination of inflammatory bowl diseases and disorders in clinics. It is an effective and efficient non-invasive procedure for the visualization of the entire small intestine of a patient. It enables a physician to diagnose the abnormality of the digestive system at the earliest for prognosis. The manual examination of the WCE images, frame by frame is a tedious task for physicians. A physician requires two to three hours for the investigation of WCE images of one patient for the accurate diagnosis and staging of the diseases. Therefore, intelligent approaches are designed and implemented in the past couple of decades to provide support for endoscopists to analyze the images. In this paper, a survey on different image processing techniques and machine learning approaches used for the accurate and quick examination of WCE images has been presented. The issues behind the computational approaches for processing WCE images and videos are also analyzed with future directions.*

Keywords: *Gastrointestinal tract, esophagus, Computer Aided Diagnosis, Endoscopy.*

I. INTRODUCTION

The longest portion of the intestinal tract is the small intestine which is a vital organ for the absorption of nutrients.

Abbreviations: Gastrointestinal Tract; CE, Wireless Capsule Endoscopy; AVM, Arteriovenous Malformations; CAD, Computer Aided Diagnosis; AI; Artificial Intelligence; FOV, Field of View; SVM, Support Vector Machine; TPF, True Positive Fraction; FPF, False Positive Fraction; CLAHE, Contrast Limited Adaptive Histogram Equalization; FCM, Fuzzy C-Means ; RMSE, Root Mean Square Error;

LBP, Local Binary Pattern; IT, Insertion Time; WT, Withdrawal Time; CWT, Clear Withdrawal Time; COWT, Clear Operation-Free Withdrawal Time; RX, Reed-Xiaoli; OS, Oscillating Search; SFFS, Sequential Forward Floating Search; GA, Genetic Algorithm; IPQ, Portuguese Institute of Oncology; BEEMD, Bidimensional Ensemble Empirical Mode Decomposition; IMF, Intrinsic Mode Functions; CR, Compression Ratio; PSNR, Peak-Signal to Noise Ratio; SUSAN, Smallest Univalue Segment Assimilating Nucleus; SSIM, Structural Similarity Index Measurement; PDD, Photo Dynamic Diagnostics; SIFT, Scale Invariant Feature Transform; PLSA, Probabilistic Latent Semantic Analysis; SVM-SFFS, SVM with Sequential Forward Floating Selection; SVM-RFE, SVM with Recursive Feature Elimination; AGF, Autocorrelation Gabor Features; AHT, Autocorrelation Homogeneous Texture; HMA, Hierarchical Multi-affine Algorithm; MIS, Minimally Invasive Surgery; CR-ULBP, Color Rotation - Uniform rotation invariant Local Binary Pattern; DCT-LAC, Discrete Curvelet Transform with Differential Lacunarity; CH, Chromo endoscopy; NBI, Narrow-Band Imaging DSC, Dice Similarity Coefficient; ROI, Region of Interest; DCT, Discrete Cosine Transform; ASM, Angular Second Moment; CON, Contrast; COR, Correlation; ENT, Entropy; VAR, Variance; IDM, Inverse Difference Moment; SRE, Short Runs Emphasis; LRE, Long Runs Emphasis; GLN, Gray Level Non uniformity; RLN, Run Length Non uniformity; RPC, Run Percentage; RBCT, Ridgeness Based Circle Test; IDV, Intestinal Direction Vector; GND, Glottal Neighbourhood Descriptor; VHOG, Variant Histogram of Oriented Gradient; ORA, Overall Recognition Accuracy; SALLC, Saliency and Adaptive Locality Constrained Linear Coding; MSRCR, Multi-Scale Retinex with Colour Restoration;

Small bowl is a part of the intestine that lies between the stomach and the colon[1]. It is a challenging task for the physicians to manually examine the causes for abnormality of gastrointestinal (GI) tract that originates in the small bowel. It is hard to reach with instruments either through the mouth or through the anus because it is located between the stomach and the large bowel[2]. The small bowel is more than 17 feet long, so the X-ray technology is not suitable to pinpoint exact locations of abnormalities of small intestine[3].

The abnormal blood vessels, known as AVMs (Arteriovenous Malformations) are located within the wall of the small bowel. They are the major causatives for the bleeding in the small bowel and they are invisible in standard X-rays. Various destructive illnesses such as Crohn's disease, obscure GI bleeding, Barrett's esophagus, sceliac disease, tumor, Cancer, ulcer infections, and diverticular occur due to the AVMs in different regions of the GI tract[4].In earlier periods, to examine the GI tract, wired endoscopy was used. In wired endoscopy, long cable was entered into the GI tract to diagnose the diseases of small bowel. But patients feel pain and discomfort due to itssize. Also, wired endoscopy could not reach the significant part of the small intestine[3].

To address the issues behind the wired endoscopy, the first Wireless Endoscopy Pillcam was manufactured by "Given Imaging" in 2000 to visually monitor the entire GI tract[5]. This swallobale pill incorporated a little camera, an imaging sensor, and a remote network feature that permits the transmission of pictures and recordings of the GI tract. The information can be received by the specialists at a remote location. This innovation is extremely powerful since it offers pain-free and accurate diagnosis of the GI tract effectively[6].

Generally, WCE captures a minimum of three or more pictures of GI tract for every second. Normally, the whole procedure to examine GI tract will take around 8 hours until the batteries debilitate. Consequently, it will deliver more than 50,000 pictures for every patient. These images are compacted and transmitted to a portable medium such as data recorder attached to the patient's waist using radio frequency link. Then the WCE image data are downloaded into a PC workstation and endoscopists will physically examine at these images frame by frame to recognize regions with abnormal conditions and severity of the patient. To evaluate the WCE images of one patient by a endoscopist, two to three hours are generally required, which is a time-consuming and laborious process. Therefore, it is necessary to design and implement an intelligent CAD system to support endoscopists for diagnosis[7]

Digital image processing is the emerging field that analyze digital images through the use of computational model. The major goal of biomedical imaging techniques is to analyze the images for both diagnostic and therapeutic purposes. Medical image processing algorithms process ambiguous, missing, inconsistent, redundant and distorted image data only for some extent. The features extracted from the digital images are used to diagnose the disease. The images taken from X-ray, ultrasound, MRI, nuclear medicine and optical imaging technologies are enhanced using image processing technology to help the physicians for the identification and staging the diseases quickly and accurately. The various image processing techniques such as image pre-processing, image segmentation, edge detection, feature extraction, morphological image processing techniques are employed in the WCE images to predict the diseases. Similarly, image reconstruction and modelling techniques provide quick examination of 2D signals and they also help to create 3D images. The available image processing software is able to analyze the medical images automatically and identify the suspicious regions even when they are not apparent to the eye of an expert[8].

In the medicine field, image processing technology visualizes the interior portions of the body to help the specialists for easy diagnosis. Similarly, it helps the specialists to make keyhole medical surgeries by reaching the inner parts of the body without harming the body too much[9].

The Broad utilization of computerized imaging in medicine field requires sharp, clear and noise free medical images to diagnose the diseases accurately[10]. Even though the progression in the technologies produces digital medical images with higher resolution and quality, removing of noise in the digital images remains one of the major challenges task in the study of medical imaging[11]

Computer Aided Diagnosis (CAD) is an interdisciplinary technology which combines multiple concepts such as artificial intelligence (AI), computer vision, and medical image processing. The main goal of CAD system is to identify the abnormal and pathology regions at an earlier stage for prognosis. CAD systems can be utilized to enhance the WCE images and also to diagnose the disease accurately[12]. Machine learning techniques are employed in CAD systems for endoscopy image processing and analysis. Some of the AI techniques are also involved in medical image processing such as Decision Support Systems, Neural Networks, Expert Systems, Knowledge Based Systems, Fuzzy Logic and Systems, Neuro-Fuzzy Systems, Data Mining, Evolutionary and Genetic (or bioinspired) Algorithms, Semantic Nets etc[8]. Endoscopic images possess rich information[1], which is used for abnormality detection through machine learning techniques. The Chromatic or spatial domain techniques has been applied for detecting disease patterns. But applying these techniques individually may lead to inaccurate diagnosis. For example, identification of bleeding region and inflammation may possess different texture and color features[13]. As far as the GI tract diseases are concerned, it is essential to utilize soft computing techniques at the maximum for better and accurate analysis.

The rest of the paper is organized as follows: a systematic review of proposed computational approaches for efficient diagnoses of the WCE images has been conducted and presented in section II with the issues faced for diagnosing the disease using endoscopy images. The paper is concluded in Section III with possible further research direction.

II. COMPUTATIONAL APPROACHES FOR COMPUTER ASSISTED DIAGNOSIS OF GI TRACT DISEASES THROUGH WIRELESS CAPSULE ENDOSCOPY

The most common threat for human health is the diseases which affect Gastrointestinal tract (GI) such as cancer and bleeding in intestine. A research at Hong Kong hospital [2003] reported that 18% of Cancer deaths in Hong Kong in 2000 are GI related colon and stomach cancers[14]. It is necessary to detect the disease in GI tract at an early stage for prevention. Wireless Capsule Endoscopy is more suitable for the examination of the entire GI tract. Machine learning approaches have been used to identify and staging the severity of disease in WCE images. An elaborate review of computational approaches for diagnosis of diseases in WCE images are presented in table 1.

A. ISSUES RELATED TO DIAGNOSIS OF ENDOSCOPIC IMAGES

From the review of literature, the following issues are identified in processing and diagnosis of WCE using computational approaches.

The Issues Related to WCE Image Analysis

- WCE produces approximately 55,000 images per examination. Due to the vast amount of images created during WCE, even experienced physicians need much longer time to identify the abnormalities in the images. Therefore, the inspection of the images by a physician is the most time consuming process.
- The extraction of informative frames from original WCE videos is a difficult task since huge amount of time is required for analyzing each and every frame for diagnosis.
- A video recorded by WCE to examine GI tract contains more than 50,000 frames. Manual analysis of these frames is highly a tedious and times consuming task. Several researches generate abstractive and summarization approaches to reduce the reading time of the physician in long WCE video. However this approach selects a few sample frames from the entire video. Hence lose some informative frames related to disease diagnosis.

Table 1. WCE Diagnosis Review Methods and Results

<table>
<tr><th>AUTHOR</th><th>YEAR</th><th>METHODOLOGY</th><th>Findings</th><th colspan="3">PARAMETER</th></tr>
<tr><td>Warren . Smith et al., [15]</td><td>1992</td><td>Distortion Correction Algorithm</td><td>Distortion correction</td><td colspan="3">Distortion Areas
Mean – 0.1898cm^2
Standard Deviation – 0.0068 cm^2
No Distortion Areas
Straight Line of Constant Area = 0.1963 cm^2.</td></tr>
<tr><td>K. Vijayan Asari et al., [16]</td><td>1999</td><td>Least Squares Estimation-Based Approach</td><td>Distortion correction</td><td colspan="3">Avg. Mean Error Before Distortion Correction – 1.35
Avg. Mean Error after Distortion Correction – 0.28</td></tr>
<tr><td rowspan="4">Taosong He et al., [17]</td><td rowspan="4">2001</td><td rowspan="4">Reliable Path Generation Algorithm</td><td rowspan="4">Finds reliable path for the complete Examinations of human organ</td><td></td><td>Reliable Path</td><td>Time</td></tr>
<tr><td>I Dataset</td><td>363 Voxels</td><td>109 Seconds</td></tr>
<tr><td>II Dataset</td><td>1378 Voxels</td><td>23 Seconds</td></tr>
<tr><td>III Dataset</td><td>2741 Voxels</td><td>270 Seconds</td></tr>
<tr><td>James P. Helferty et al., [18]</td><td>2001</td><td>Distortion-Correction Technique (DCT) based on least square approach</td><td>Distortion Correction</td><td colspan="3">Average Error – 0.0729
Standard Deviation Error – 0.003
Maximum Error – 0.261</td></tr>
<tr><td>Baopu Li et al., [19]</td><td>2006</td><td>Tensor Based Diffusion Method</td><td>Contrast Enhancement of WCE images</td><td colspan="3">Qualitatively measured</td></tr>
</table>

<table>
<tr><td>Baopu Li et al., [21]</td><td>2007</td><td>Local Color Feature extraction using color histogram</td><td>Normal or Abnormal detection from gastrointestinal images</td><td>Sensitivity=65.2%, Specificity=82.5%.</td></tr>
<tr><td>Baopu Li et al., [22]</td><td>2007</td><td>A Forward and Backward Anisotropic Diffusion Method based on the contrast space</td><td>WCE Image Enhancement</td><td><table><tr><td colspan="5">I1 – Original Image , I4 – Proposed Method</td></tr><tr><td></td><td>I1</td><td>I2</td><td>I3</td><td>I4</td></tr><tr><td>AUC</td><td>0.792</td><td>0.810</td><td>0.882</td><td>0.944</td></tr></table></td></tr>
<tr><td>Yu Cao et al., [9]</td><td>2007</td><td>Region growing algorithm based on texture features</td><td>Detection and diagnosis of therapeutic operations in Colonoscopy videos</td><td>Accuracy
For Cable Images – 92%
For Non-Cable Images – 93%</td></tr>
<tr><td>S. Tsevas et al., [25]</td><td>2008</td><td>Fuzzy C-Means (FCM) FCM, Non-negative Lagrangian Relaxation (NLR) and Symmetric Non-Negative Matrix Factorization (SymNMF)</td><td>Video frames reduction in WCE images</td><td>For a threshold value equal to 1E-2 , the total number of frames was reduced down to the 10% of the initial one.</td></tr>
<tr><td>Luís A. Alexandre et. al., [26]</td><td>2008</td><td>Color and Position based method (RGB + XY)</td><td>Polyp detection</td><td>AUC – 94.87%</td></tr>
<tr><td>Poh Chee Khun et al., [30]</td><td>2009</td><td>SVM and Neural Network</td><td>Classification of Informative and non informative frames</td><td><table><tr><td colspan="2" rowspan="2">Feature / Method</td><td colspan="2">Informative Frames</td><td colspan="2">Bleeding Frames</td></tr><tr><td>Color Feature</td><td>Texture Feature</td><td>Color Feature</td><td>Texture Feature</td></tr><tr><td rowspan="2">Accuracy (%)</td><td>SVM</td><td>94.10</td><td>73.85</td><td>99.41</td><td>92.32</td></tr><tr><td>NN</td><td>93.44</td><td>70.41</td><td>98.97</td><td>80.30</td></tr><tr><td rowspan="2">Time (Sec)</td><td>SVM</td><td>0.7125</td><td>6.7666</td><td>0.5100</td><td>2.1236</td></tr><tr><td>NN</td><td>1.0329</td><td>2.3869</td><td>1.2163</td><td>1.3380</td></tr></table></td></tr>
<tr><td>Jung Hwan Oh et al., [31]</td><td>2009</td><td>Video segmentation based on camera motions and 5 Quality Metrics</td><td>Quality Metrics for measuring quality of Colonoscopy</td><td>Effectiveness of SHOT Detection
Avg. Precision – 0.809
Avg. Recall – 0.873
Effectiveness of PHASE Detection
Time Difference between Actual Phase Boundary (APB) and Detected Phase Boundary (DPB) is 00 Min:15 Sec</td></tr>
<tr><td>Li Liu et al., [32]</td><td>2009</td><td>Complementary Orientation Approach</td><td>Capsule Endoscope Localization</td><td><table><tr><td>Given Rotation Angle</td><td>Calculated Rotation Angle</td><td>Error</td></tr><tr><td>5^o</td><td>4.9327^o</td><td>0.067^o</td></tr><tr><td>10^o</td><td>9.8207^o</td><td>0.179^o</td></tr><tr><td>15^o</td><td>14.5972^o</td><td>0.403^o</td></tr><tr><td>20^o</td><td>21.7749^o</td><td>1.775^o</td></tr><tr><td>25^o</td><td>24.1724^o</td><td>0.829^o</td></tr><tr><td>30^o</td><td>-0.52784^o</td><td>Big Error</td></tr></table></td></tr>
</table>

<table>
<tr><td rowspan="1">Barbara Penna et. al., [33]</td><td>2009</td><td>Multi Stage blood detection Model</td><td>Bleeding patterns detection in WCE image</td><td colspan="5">Sensitivity - 9%
Specificity - 88%
False Alarm Rate (FAR)-8%
Missed Detection Rate (MDR) – 3%</td></tr>
<tr><td rowspan="3">Sousa, A et. al., [34]</td><td rowspan="3">2009</td><td rowspan="3">Adapted Color features combined with Local Binary Patterns (LBP)</td><td rowspan="3">Gastric Regions classifications</td><td>Features / Classifiers</td><td>DT</td><td>NB</td><td>KNN</td><td>SVM</td></tr>
<tr><td>Full HS + LBP(8,2)</td><td>88.1%</td><td>68.2%</td><td>84.1%</td><td>88.6%</td></tr>
<tr><td>Body2_HS +LBP (8,2)</td><td>86.4%</td><td>77.3%</td><td>85.8%</td><td>90.9%</td></tr>
<tr><td rowspan="4">Michael Hafner et al., [35]</td><td rowspan="4">2010</td><td rowspan="4">Sequential Forward Floating Search (SFFS), Oscillating Search (OS), and a Genetic Algorithm (GA)</td><td rowspan="4">Classification of Endoscopic images</td><td colspan="5">Classification Accuracy (RDA Classifier)</td></tr>
<tr><td></td><td>SFFS</td><td colspan="2">GA</td><td>OS</td></tr>
<tr><td>Two Classes Case</td><td>96.58 %</td><td colspan="2">96.6%</td><td>96.9%</td></tr>
<tr><td>Six Classes Case</td><td>93.68%</td><td colspan="2">95.23%</td><td>86.8%</td></tr>
<tr><td>Yi Wang et al., [38]</td><td>2010</td><td>Edge Profile-Based Appendiceal Orifice Image Detection Algorithm</td><td>Appendix/Nonappendix videos Classification</td><td colspan="5">Overall Classification Accuracy - 91.30%
Appendix Videos Accuracy – 93%
Non Appendix Videos – 87.5%</td></tr>
<tr><td rowspan="3">Vasileios Charisis et al., [39]</td><td rowspan="3">2010</td><td rowspan="3">Bidimensional Ensemble Empirical Mode Decomposition (BEEMD)

Classification
SVM , Discriminate Analysis (DA)</td><td rowspan="3">Classification of Ulcer and Normal WCE images</td><td colspan="2">Method / Channel</td><td>Red Channel</td><td>Green Channel</td><td>Blue Channel</td><td>RGB Channel</td></tr>
<tr><td rowspan="2">Accuracy</td><td>SVM</td><td>90.7</td><td>94.9</td><td>89.4</td><td>94.2</td></tr>
<tr><td>DA</td><td>88.6</td><td>95.65</td><td>90.7</td><td>95.75</td></tr>
<tr><td>Fernando Vilariño et. al., [40]</td><td>2010</td><td>Cascade System for the automatic Detection of Intestinal Contractions using WCE</td><td>Detection of Phasic intestinal contractions</td><td colspan="5">Average (Video1 to Video 10) Sensitivity – 70.08%
Specificity – 99.12%
False Alarm Ratio (FAR) – 48.71%Precision – 60.26%</td></tr>
<tr><td>T.H.Khan et al., [41]</td><td>2011</td><td>YEF Colour Space</td><td>Compression of WCE images</td><td colspan="5">Average PSNR = 45.19 dB</td></tr>
<tr><td>Alexandros Karargyris et al., [42]</td><td>2011</td><td>SUSAN (Smallest Univalue Segment Assimilating Nucleus) Edge Detector and Log Gabor Filters</td><td>Polyp and Ulcer detection</td><td colspan="5">Polyp Detection
Sensitivity-100%
Specificity-67.5%
Ulcer detection
Sensitivity-75%
Specificity-73.3%</td></tr>
<tr><td rowspan="5">Alexander Behrens et. al., [43]</td><td rowspan="5">2011</td><td rowspan="5">Fidelity Score for quantitative image quality assessment based on Structural Similarity Index Measurement (SSIM)</td><td rowspan="5">Image quality assessment</td><td colspan="5">Fidelity Score</td></tr>
<tr><td colspan="2">Blending Technique</td><td colspan="2">Cystoscopy</td><td>Phantom</td></tr>
<tr><td colspan="2">Alpha-Blending</td><td colspan="2">0.6936</td><td>0.3124</td></tr>
<tr><td colspan="2">Pyramid Blending</td><td colspan="2">0.7125</td><td>0.3120</td></tr>
<tr><td colspan="2">Non-Linear Blending</td><td colspan="2">0.8469</td><td>0.6982</td></tr>
<tr><td>Yao Shan et al., [44]</td><td>2012</td><td>Scale Invariant Feature Transform (SIFT) and Probabilistic Latent Semantic Analysis (PLSA)</td><td>WCE video Segmentation of digestive tract</td><td colspan="5">The computation time for the testing is 1.375s per frame while for the training is 15.338s per frame for a typical codebook size of 600</td></tr>
<tr><td>Rajesh Kumar et al. [45]</td><td>2012</td><td>Supervised Statistical Classification methods</td><td>Assessment of Crohn's Disease Lesions</td><td colspan="5">Avg. Accuracy
Normal – 80.2
Lesion – 89.3</td></tr>
</table>

<table>
<tr><td>Santi Segui et al. [46]</td><td>2012</td><td>Two fold system for Categorization and Segmentation of Intestinal Content Frames</td><td>Segmentation of intestinal content in WCE images</td><td colspan="5">Avg. Overlap Area – 83.29%</td></tr>
<tr><td rowspan="3">Baopu Li et al., [47]</td><td rowspan="3">2012</td><td rowspan="3">SVM with Sequential Forward Floating Selection (SVM-SFFS) and SVM with Recursive Feature Elimination (SVM-RFE)</td><td rowspan="3">Tumour recognition</td><td></td><td>Acc.</td><td colspan="2">Sen.</td><td>Spec.</td></tr>
<tr><td>SVM+SFFS</td><td>92.4</td><td colspan="2">96.2</td><td>88.6</td></tr>
<tr><td>SVM+RFE</td><td>87.2</td><td colspan="2">91.3</td><td>83.1</td></tr>
<tr><td rowspan="4">Farhan Riaz et. al., [48]</td><td rowspan="4">2012</td><td rowspan="4">Texton Autocorrelation Gabor Features (AGF) Descriptors and Autocorrelation Homogeneous Descriptors (AHT)</td><td rowspan="4">Classification of images such as normal, cancerous and precancerous</td><td colspan="5">Accuracy</td></tr>
<tr><td></td><td colspan="2">CH Images</td><td colspan="2">NBI Images</td></tr>
<tr><td>Texton-AGF</td><td colspan="2">0.82</td><td colspan="2">0.85</td></tr>
<tr><td>AHT</td><td colspan="2">0.83</td><td colspan="2">0.85</td></tr>
<tr><td>Gustaw A. Puerto Souza et al., [49]</td><td>2013</td><td>Hierarchical Multi-affine Algorithm (HMA)</td><td>Feature Matching</td><td colspan="5">Sensitivity – 0.85
Avg. Time – 0.05S</td></tr>
<tr><td>Vasileios S. Charisiset al., [50]</td><td>2013</td><td>Color Rotation - Uniform rotation invariant Local Binary Pattern (CR – ULBP) approach</td><td>Ulcer detection</td><td colspan="5">Sensitivity – 70%, Accuracy – 75%
Specificity – 80%</td></tr>
<tr><td>Alexis Eid et al., [51]</td><td>2013</td><td>Discrete Curvelet Transform with Differential Lacunarity (DCT-LAC) detection scheme</td><td>Ulcer detection</td><td colspan="5">Avg. Accuracy – 81.89%
Avg. Sensitivity – 80.54%
Avg. Specificity – 81.89%</td></tr>
<tr><td>Sonu Sainju et al., [52]</td><td>2013</td><td>Color Feature Extraction using first order histogram of RGB Plane</td><td>Bleeding detection</td><td colspan="5">The highest classification accuracy of 89.09% was achieved with the feature sizes (m) 3,4,5,6</td></tr>
<tr><td rowspan="6">Farhan Riaz et. al., [53]</td><td rowspan="6">2013</td><td rowspan="6">Normalized Cuts approach</td><td rowspan="6">Segmentation</td><td rowspan="2">Features</td><td colspan="2">CH Images</td><td colspan="2">NBI Images</td></tr>
<tr><td>DSC</td><td>F-Measure</td><td>DSC</td><td>F-Measure</td></tr>
<tr><td>LUV + TEX</td><td>0.6</td><td>0.58</td><td>0.71</td><td>0.69</td></tr>
<tr><td>LUV + CRE</td><td>0.58</td><td>0.56</td><td>0.64</td><td>0.62</td></tr>
<tr><td>TEX + CRE</td><td>0.64</td><td>0.62</td><td>0.85</td><td>0.83</td></tr>
<tr><td>LUV+TEX+ CRE</td><td>0.63</td><td>0.61</td><td>0.84</td><td>0.82</td></tr>
<tr><td>Alexander V. Mamonov et al., [54]</td><td>2014</td><td>Binary Classifier with Preselection algorithm</td><td>Polyps Classification</td><td colspan="5">Specificity - 90.2%
Sensitivity - 47.4%.</td></tr>
<tr><td>Yanan Fu et al., [55]</td><td>2014</td><td>Superpixel Segmentation with SVM</td><td>Bleeding Detection</td><td colspan="5">Accuracy – 95%
Time – 0.54 Sec</td></tr>
<tr><td>Adam Brzeski [59]</td><td>2014</td><td>Color Descriptor for bleeding detection in Endoscopic images</td><td>Blood color detection</td><td colspan="5">Fraction of bleeding images with features present
Exact blood color descriptor for the test set - 92%
Close blood color descriptor - 97%</td></tr>
</table>

<table>
<tr><td>Hai Vu et al., [60]</td><td>2014</td><td>Automatic Segmentation method based on a statistical operator such as Local Mean Image with diffusion techniques.</td><td>Reddish lesions segmentation</td><td colspan="4">The average probability of detection (υ_d) - 92
The average probability of false alarm (υ_{far}) - 10
The average probability of under segmentation (υ_{un}) – 16</td></tr>
<tr><td>0P.Shanmuga Sundaram et al., [61]</td><td>2014</td><td>Grow Cut Algorithm</td><td>Segmentation of WCE images</td><td colspan="4">Qualitatively Measured</td></tr>
<tr><td>Rosdiana Shahril et al., [62]</td><td>2014</td><td>Discrete Cosine Transform (DCT)</td><td>Image enhancement</td><td colspan="4">Avg. PSNR – 18.56
Avg. Sharpness – 4.80</td></tr>
<tr><td>Tomoyui Hiroyasu et al., [64]</td><td>2014</td><td>Texture Analysis Method such as Co-Occurrence Matrix And Run Length Matrix</td><td>Lesion Discrimination</td><td colspan="4">7 out 8 Lesion zone were correctly identified.</td></tr>
<tr><td>Santi Segui et al. [65]</td><td>2014</td><td>Structured Output Support Vector Machine(SO-SVM)</td><td>Detection of wrinkle frames</td><td colspan="4">Accuracy – 92.38
Precision – 91.85
Recall – 84.48
AUC – 96.07</td></tr>
<tr><td>Bing xiong Lin et al., [66]</td><td>2015</td><td>Ridgeness based Circle test (RBCT) and Ridgeness-Based Branching Segment Detection (RBSD)</td><td>Vessel and Lumen detection
Overall</td><td colspan="4">Repeatability Score
RBCT - 0.54
RBSD - 0.58</td></tr>
<tr><td>Dan Wang et al., [74]</td><td>2015</td><td>Intestinal Direction Vector (IDV) Acquisition Method</td><td>Lumen detection Precision</td><td colspan="4">Precision – 955, Sensitivity - 98.1
Accuracy - 96.2</td></tr>
<tr><td rowspan="3">Oliver Gloger et al., [10]</td><td rowspan="3">2015</td><td rowspan="3">Glottal Neighborhood Descriptor (GND)</td><td rowspan="3">Segmentation</td><td></td><td>Mean Dice</td><td>Mean Area Error</td><td>Processing Time (Sec)</td></tr>
<tr><td>Video Set I (Mild Pathologies)</td><td>0.89</td><td>0.07</td><td>1.81</td></tr>
<tr><td>Video Set II (Severe Pathologies)</td><td>0.85</td><td>0.1</td><td>2.17</td></tr>
<tr><td>T. Ghosh et. al., [77]</td><td>2015</td><td>YIQ (luminance-Y, chrominance-IQ: in phase-I and quadrature-Q) color Scheme</td><td>Ulcer Detection</td><td colspan="4">Sensitivity – 93.50%, Specificity – 94%
Accuracy – 93.90%</td></tr>
<tr><td>Seung-Hwan Bae et. al., [81]</td><td>2015</td><td>Adaboosting and up/down data sampling.</td><td>Polyp detection</td><td colspan="4">AUC – 50.49%</td></tr>
<tr><td>Yixuan Yuan et. al., [82]</td><td>2015</td><td>Saliency Detection Method</td><td>Ulcer Detection</td><td colspan="4">Sensitivity – 94.12%, Specificity – 91.18%
Accuracy – 92.65%</td></tr>
<tr><td>Yixuan Yuan et. al., [86]</td><td>2015</td><td>Word based color histogram</td><td>Bleeding frame Detection</td><td colspan="4">Accuracy – 95.75%, Sensitivity – 92%, Specificity – 96.50% Time – 293.43 Sec</td></tr>
<tr><td>Reeha et al., [91]</td><td>2016</td><td>Undecimated Double Density Dual tree – Discrete Wavelet Transform (UDDDT-DWT)</td><td>Bleeding Detection</td><td colspan="4">Accuracy – 99.5%, Sensitivity – 99%
Specificity – 100%</td></tr>
<tr><td>Shuai Wang et al., [92]</td><td>2016</td><td>Online Metric Learning</td><td></td><td colspan="4">AUC – 0.93
Time – 0.17 Min</td></tr>
</table>

<table>
<tr><td>Chun-Rong Huang et al., [94]</td><td>2016</td><td>A Hierarchical Heterogeneous Descriptor Fusion Support Vector Machine (HHDF-SVM) Framework</td><td>Diagnosis of Gastroesophageal Reflux Disease (GERD)</td><td colspan="3">Accuracy –93.2%, TPR–94.9%
TNR–92.6%</td></tr>
<tr><td>Xiao Wu et al., [95]</td><td>2016</td><td>The Piecewise Parallel Region Detection (PPRD) method and Uncurled Tubular Region</td><td>Hookworm detection from Pylorus</td><td colspan="3">Accuracy – 78.2%, Sensitivity – 77.2%
Specificity – 77.9%</td></tr>
<tr><td>Ravi Shrestha et al., [96]</td><td>2016</td><td>Automated Adaptive Brightness (AB) algorithm with Sigmoid Function</td><td>To control the brightness level of LEDs to be used in wireless capsule endoscopy system S</td><td colspan="3">Power Consumption
Focus Value – 8.89
Total Current – 35.7
LED Current – 4.2</td></tr>
<tr><td>Shang-Bo Zhou et al., [97]</td><td>2016</td><td>Support Vector Machine classifer</td><td>Bleeding Detection</td><td colspan="3">Sensitivity – 98.53%,Specificity – 93.60%
Accuracy – 96.36%</td></tr>
<tr><td>A. K. Kundu et al., [100]</td><td>2016</td><td>Image Histogram</td><td>Ulcer Detection</td><td colspan="3">Sensitivity – 85.13%, Specificity – 90.42%
Accuracy – 87.23%</td></tr>
<tr><td rowspan="5">Rosdiana Shahril et. al., [103]</td><td rowspan="5">2016</td><td rowspan="5">Discrete Cosine Transform with Anisotropic Contrast Diffusion method</td><td rowspan="5">Preprocessing</td><td>Image</td><td>PSNR</td><td>Sharpness</td></tr>
<tr><td>Patient A</td><td>16.18249</td><td>6.14052</td></tr>
<tr><td>Patient B</td><td>17.45708</td><td>7.70441</td></tr>
<tr><td>Patient C</td><td>17.98542</td><td>3.70399</td></tr>
<tr><td>Patient D</td><td>22.57574</td><td>2.42673</td></tr>
<tr><td>Yixuan Yuan et. al., [104]</td><td>2016</td><td>Improved Bag of Feature (BoF) method</td><td>Polyp Detection</td><td colspan="3">Sensitivity – 94.54%
Specificity – 93.20%
Accuracy – 93.20%</td></tr>
<tr><td>Corina Barbalaa et. al., [105]</td><td>2016</td><td>Anisotropic and Matched filters (MFs) based approach</td><td>Larygneal Tumour Detection</td><td colspan="3">Sensitivity – 70%, Specificity- 87%, Accuracy – 78%, Dice – 76%</td></tr>
<tr><td>Jorge Bernal et al. [108]</td><td>2017</td><td>Comparative Validation of Polyp Detection Methods</td><td>Polyp Detection</td><td colspan="3">---</td></tr>
<tr><td>Farhan Riaz et al., [109]</td><td>2017</td><td>IGabor Filter method</td><td>Cancer Detection and melanoma classification</td><td colspan="3"><u>IGabor with 1NN classifier</u>
TP Rate – 0.81 , ROC Area – 0.70
<u>IGabor with NB classifier</u>
TP Rate – 0.85 , ROC Area – 0.89
<u>IGabor with SVM classifier</u>
TP Rate – 0.87 , ROC Area – 0.91
<u>IGabor with DT classifier</u>
TP Rate – 0.82 , ROC Area – 0.71</td></tr>
<tr><td>Yixuan Yuan et al., [115]</td><td>2017</td><td>Saliency and Adaptive Locality Constrained Linear Coding (SALLC) algorithm</td><td>Abnormality Detection in WCE images</td><td colspan="3">ORA (Overall Recognition Accuracy) – 88.61
Processing Time - 1917.35 Sec</td></tr>
<tr><td>Meryem Souaidi et. al., [118]</td><td>2017</td><td>Local Binary Pattern (LBP) and Laplacian Pyramid Transform</td><td>Ulcer region Detection</td><td colspan="3">Accuracy – 95.61%
Sensitivity – 97.68%
Specificity – 94.40%
AUC – 0.95846</td></tr>
</table>

<table>
<tr><td>Antonios Perperidis et al., [119]</td><td>2017</td><td>Gaussian Mixture Model with Principal Component Analysis (PCA)</td><td>Detection of Uninformative Frames</td><td>Sensitivity – 93.0%
Specificity – 92.6%</td></tr>
<tr><td>Farah Deeba et. al., [120]</td><td>2017</td><td>Saliency-Aided Visual Enhancement (SAVE)</td><td>Lesion Detection</td><td>AUC - 94.91%.
Sensitivity - 100%
Specificity–65.45%</td></tr>
<tr><td>Isabel N. Figueiredo et. al., [121]</td><td>2017</td><td>The Image Registration Approach</td><td>bleeding identification in small bowel images</td><td>Qualitatively measured</td></tr>
<tr><td>Vasileios S. Charisis et. al., [122]</td><td>2017</td><td>Hybrid adaptive filtering (HAF) and differential lacunarity (DL) (HAF-DL) scheme</td><td>Crohn’s disease lesion detection</td><td>Mean Sensitivity – 93.5%</td></tr>
<tr><td>Tonmoy Ghosh et al., [123]</td><td>2018</td><td>CHOBS: Color Histogram of Block Statistics</td><td>Bleeding Detection</td><td>Accuracy - 99.15%</td></tr>
<tr><td>Atefe Rajaeefar et al., [124]</td><td>2018</td><td>Lossless Image Compression by Content-Based Classification of Image Blocks</td><td>Image Compression</td><td>Compression Ratio for Videos – 10.93
Compression Ratio for Push Endoscopy images – 2.50</td></tr>
<tr><td>Ahmed Mohammed et al., [125]</td><td>2018</td><td>Stochastic sampling Techniques</td><td>WCE Image Enhancement</td><td>Weighted-Level Framework (WLF) [33] – 1.48
Structural Similarity Index (SSIM) [34] – 0.92
Feature-Similarity (FSIM) Index [35] - 3.03
Information Content Weighted Structural Similarity Measure (IW-SSIM) – 0.93</td></tr>
<tr><td>Pedro N. Figueiredo et al., [128]</td><td>2018</td><td>A binary classifier and a threshold-based methods</td><td>Polyp Detection</td><td><table>
<tr><th>Method</th><th>Sens</th><th>Spec</th><th>Acc</th></tr>
<tr><td>Method1</td><td>83.7 %</td><td>66.6%</td><td>74.3%</td></tr>
<tr><td>Method 2</td><td>61.6%</td><td>61.3%</td><td>63.2%</td></tr>
<tr><td>Method 3</td><td colspan="3">Not implemented, since no frames were available without polyps</td></tr>
</table></td></tr>
<tr><td>M. Hajabdollahi et al., [130]</td><td>2018</td><td>CNN and MLP</td><td>Informative frames detection</td><td><table>
<tr><th>Method</th><th>DICE</th><th>AUC</th></tr>
<tr><td>Quantized MLP</td><td>0.831</td><td>0.974</td></tr>
<tr><td>Full Precision MLP</td><td>0.861</td><td>0.983</td></tr>
<tr><td>Quantized CNN</td><td>0.846</td><td>0.978</td></tr>
<tr><td>Pruned Quantized CNN</td><td>0.869</td><td>0.985</td></tr>
<tr><td>Full Precision CNN</td><td>0.890</td><td>0.984</td></tr>
</table></td></tr>
<tr><td>Isabel N. Figueiredo et al., [133]</td><td>2018</td><td>Multiscale Affine And Elastic Image Registration (MEIR)</td><td>wireless capsule endoscope localization</td><td>Mean Scale Error - 0.0464
Mean Rotation Error - 4.1111</td></tr>
<tr><td>Mingzhu Long [134]</td><td>2018</td><td>Adaptive Fraction Gamma Transformation with Color Restoration (AFGT-CR)</td><td>WCE Image Enhancement</td><td>IRMLE – 1.62
CEF – 1.35
LOE - 1.91
Time – 0.0315 Sec</td></tr>
<tr><td>Meryem Souaidi et al., [135]</td><td>2018</td><td>Multi-Scale approach based on Completed Local Binary Patterns, And Laplacian Pyramid (MS-CLBP).</td><td>Ulcer Detection</td><td>Average Accuracy
Dataset 1 - 95.11%
Dataset 2 - 93.88%</td></tr>
<tr><td>Ouiem Bchir et. Al., [137]</td><td>2018</td><td>The proposed approach depends on two main components such as a feature extraction and a supervised and unsupervised learning</td><td>Bleeding detection</td><td>Accuracy – 0.9092</td></tr>
</table>

<table>
<tr><td></td><td></td><td>techniques</td><td></td><td colspan="5"></td></tr>
<tr><td>V. Vani et al., [138]</td><td>2018</td><td>Fusion of Laplacian pyramid based Image fusion of Contrast Limited Adaptive Histogram Equalization (CLAHE) and Multi-Scale Retinex with Colour Restoration (MSRCR)</td><td>WCE Image Enhancement</td><td colspan="5">SSIM – 0.99
PSNR – 25dB</td></tr>
<tr><td>Mohsen Hajabdollah et. Al., [148]</td><td>2018</td><td>quantized Multilayer Perceptron (MLP)</td><td>WCE Segmentation</td><td colspan="5">Avg. Dice Score – 0.8403</td></tr>
<tr><td>Xiaohan Xing et. Al., [151]</td><td>2018</td><td>Superpixel Color Histogram (SPCH) and subspace KNN classifier.</td><td>Bleeding Detection</td><td colspan="5">Sensitivity - 0.9851 %
Specificity – 0.9953%
Accuracy - 0.9922%</td></tr>
<tr><td rowspan="3">Paulo Coelho et al., [152]</td><td rowspan="3">2018</td><td rowspan="3">Deep Learning with UNet Architecture</td><td rowspan="3">Red Lesions Detection</td><td></td><td>ACC (%)</td><td colspan="2">TPR (%)</td><td>TNR (%)</td></tr>
<tr><td>Dataset 1</td><td>95.88</td><td colspan="2">99.56</td><td>93.93</td></tr>
<tr><td>Dataset 2</td><td>96.83</td><td colspan="2">99.09</td><td>90.68</td></tr>
<tr><td rowspan="3">Michael D. Vasilakakis et. al., [157]</td><td rowspan="3">2018</td><td rowspan="3">Distances On Selective Aggregation of chromatic image Components (DINOSARC)</td><td rowspan="3">Feature Extraction</td><td>EExperiment</td><td>AUC</td><td>Accuracy</td><td>Sensitivity</td><td>Specificity</td></tr>
<tr><td>Local Descriptor</td><td>0.813</td><td>0.809</td><td>0.680</td><td>0.814</td></tr>
<tr><td>Global Descriptor</td><td>0.815</td><td>0.818</td><td>0.512</td><td>0.908</td></tr>
<tr><td rowspan="2">Tonmoy Ghosh et. al., [160]</td><td rowspan="2">2018</td><td rowspan="2">Convolutional Neural Network (CNN)</td><td rowspan="2">Bleeding Zone Detection</td><td></td><td>Global Accuracy (%)</td><td>Mean Accuracy (%)</td><td>Mean Intersection over Union (IoU) (%)</td><td>eighted IoU (%)</td></tr>
<tr><td>Proposed</td><td>94.42</td><td>87.48</td><td>75.63</td><td>90.69</td></tr>
<tr><td>Nithin Varma Malathkar et. al., [163]</td><td>2018</td><td>Differential pulse code modulation and signed Golomb Rice code for encoding Y component and Golomb Rice code for encoding E and F components</td><td>Image Compression</td><td colspan="5">Compression Ratio (CR) - 59.7%</td></tr>
<tr><td rowspan="3">Shanhui Fan et. al., [164]</td><td rowspan="3">2018</td><td rowspan="3">Deep Learning Framework</td><td rowspan="3">Ulcer and Erosion detection in WCE images</td><td></td><td>Sen (%)</td><td colspan="2">Spec (%)</td><td>Acc(%)</td></tr>
<tr><td>Ulcer Detection</td><td>96.80</td><td colspan="2">94.79</td><td>95.16</td></tr>
<tr><td>Erosion Detection</td><td>93.67</td><td colspan="2">95.98</td><td>95.34</td></tr>
<tr><td>Tomonori Aoki et. al., [165]</td><td>2018</td><td>Convolutional Neural Network (CNN) with the Single Shot MultiBox Detector</td><td>Ulcer and Erosion detection in WCE images</td><td colspan="5">AUC – 0.958
Sensitivity – 88.2%
Specificity – 90.9%
Accuracy - 90.8%</td></tr>
<tr><td>Amit Kumar Kundu et.al., [166]</td><td>2018</td><td>Interplane Intensity Variation Profile In Normalized RGB Color Space</td><td>Bleeding Frame detection in WCE video</td><td colspan="5">Sensitivity – 95.20%
Specificity – 98.32%
Accuracy - 97.86%</td></tr>
<tr><td>Mingzhu Long et. al., [168]</td><td>2018</td><td>Adaptive Guide Image Based Enhancement (AGIE)</td><td>Image Enhancement</td><td colspan="5">The average intensity of endoscopic images was improved by 64.20% and the average local entropy (MLE) by 31.25%</td></tr>
<tr><td>Eva Tuba et. al.,</td><td>2018</td><td>Uniform Local Binary</td><td>Bleeding Detection</td><td colspan="5">Dice similarity coefficient (DSC) – 0.85</td></tr>
</table>

[173]		Pattern		Misclassification Error (ME) – 0.092
P. Sivakumar et. al., [174]	2018	Superpixel segmentation and Naive Bayes classifier.	bleeding region detection	Qualitatively measured
Xiao-dong JI et. al., [175]	2018	Back Propagation Neural Network (BPNN)	Classification	TPR – 97.43% TNR – 99.29% Accuracy – 99.09%
Romain Leenhardt et. al., [178]	2018	Convolutional Neural Network (CNN)	detection of GI angiectasia	Sensitivity – 100% Specificity – 96% Positive Predictive Value – 96% Negative Predictive Value -100%
P. Shanmuga Sundaram et al., [179]	2019	ROI based color histogram and SVM	Colon Cancer Detection in WCE Images	Sensitivity – 96% Specificity – 85.7% Accuracy - 93.1%
Qian Wang et al., [182]	2019	Ring Shape Selective (RSS) filter	Reduction of bubble-like frames	**Sensitivity** RSS-based method - 92.7% Gabor-based method – 82%
Rahul Sharma et. al., [183]	2019	RANSAC Combined with Harris Algorithm for similar frames detection.	Reduction of Redundant Frames	The Frame reduction percentage in slow motion by the proposed method was 38.2%.
Nithin Varma Malathkar et al., [187]	2019	A hybrid DPCM and new signed Golomb code with less bits skip code to compress WCE images	Image Compression	Compression Ratio – 63.4%
Muhammad Sharif et al., [193]	2019	Fusion of deep Convolutional Neural Network (CNN) and geometric features	GI Diseases Detection and classification	Accuracy - 99.54% Sensitivity - 100% Precision - 99.51%.

Pre-processing Issues in WCE Images

- Owe to non-uniform illumination conditions, the images appear darker. Visual quality in the image is also corrupted due to uneven contrast which leads to poor understanding of concerned features of the image.

There is no way to control the movement of WCE. So the pictures randomly taken by the micro-camera may be blurred or unfocused on required regions of tissues. The fast and frequent movement of the endoscope tip results in motion blur. Especially in the case of zoom-endoscopes a rather small movement of the camera may result in noticeable motion blur.Images formed with endoscopes suffer from a spatial distortion due to the wide-angle nature of the endoscope's objective lens. So it is necessary to implement distortion correction techniques for accurate diagnosis of diseases.

- The quality of the Endoscopy images is low, since the presence of undesired noise which may be caused by thermal noise produced by CCD or CMOS chips contained in modern endoscopes.

Feature Extraction or ROI Issues in processing of WCE images

- Most of the techniques available for extracting features from Endoscopic images are depend on the single domain such as Chromatic or Spatial domain. Finding disease pattern using spatial or Chromatic techniques provide partial and incomplete information which may lead to inaccurate diagnosis.
- WCE images will be ambiguous with their black in color and visible boundaries. Hence, extracted features from the images may be mirroring of those apparent visible defilements of the image.
- The different lengths and irregular shapes of edges and diverse blending orientations make more difficult to extract features and patterns for disease diagnosis.

The issues related to classification of WCE Images

- The physicians need a long time for examination to identify the normal and abnormal images. Usually, the actual number of abnormal images does not exceed 1%. While reading these pictures, clinicians have to spend two or more hours to select the abnormal and the suspect images from start to end even though most of the pictures are normal. Moreover, in order to reduce the rate of misdiagnosis, it is necessary to read repeatedly or read by other clinicians for verifying the respective diagnostic results. So, it is a time-consuming and tedious task.
- From WCE images, the number of pathology samples is usually small whereas the large numbers of samples are normal. Therefore, most of the approaches unable to deal the WCE images since the causes of data distribution are extremely imbalanced.
- The majority of abnormal WCE images are not selected effectively or the normal images are selected as the abnormalities due to the deficiencies of the diagnostic algorithm. So the presently available CAD system produces less accuracy.

The issues related to Diagnosis of WCE Images

- WCE localization plays an important role for the physicians or medical practitioners to determine the exact position of the lesion within the GI tract. Once the exact position is known, an appropriate treatment in the specified area can be performed. Localization of the capsule will also make medical procedures, such as local drug delivery and monitoring of tumors and cancers more effectively. So the efficient capsule localization techniques are necessary to address the troubles in determining the exact location of abnormalities inside the GI tract.
- It is very difficult to locate the exact location of the lesion due to the poor quality of images, presence of extraneous matters, complex structure of GI, and diverse appearances in color and texture.

III. PERFORMANCE MEASURES

The performance metric is a significant and computable measure utilized for accessing the performance of image processing algorithms quantitatively. Researchers in the past decade have used various evaluation metrics to assess the performance of their proposed methods. Various metrics were used in the literature for the diagnosis of various diseases in WCE images. The short descriptions of these measures are given here under along with their formulae.

The performance metric is a significant and computable measure utilized for accessing the performance of image processing algorithms quantitatively. Researchers in the past decade have used various evaluation metrics to assess the performance of their proposed methods. Various metrics were used in the literature for the diagnosis of various diseases in WCE images. The short descriptions of these measures are given here under along with their formulae.

The Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) were used to measure the performance of WCE image pre-processing techniques. The MSE measures the cumulative squared error between the original and the enhanced images whereas the PSNR is the ratio between the square of the maximum intensine value of the image and the mean squared error of image.

The Root-Mean-Square Error (RMSE) is a frequently used measure of the average of squared differences between enhanced and original images. It is also used to measure the performance of WCE classification and image restoration techniques. The SNR is used to measure the random and uniformly distributed noise in image pre-processing. It measures how the original images were affected by the noise. It is measured in decibels. SNR metric is used to assess image compression and pre-processing techniques of WCE images.

Mean Absolute Error (MAE) depicts the absolute differences between actual and forecast differences in WCE disease classification. MAE is applied to measure the computational efficiency of the image restoration algorithms.

Visual Information Fidelity (VIF) is one of the image quality assessments metric which measure the similarity between the original and enhanced image. VIF accesses the quality of the image enhancement algorithm and also measures the loss of human-perceivable information during the image distortion process.

The Structural Similarity Index (SSIM) is a measure of the similarity between the two different endoscopic images. It is used to compare luminance, contrast and structure of two different WCE images. Image Enhancement Factor (IEF) is the measure of the ratio between MSE of original and noisy image to the original and restored WCE image.

It is very important to detect edges in noisy images, since both the noise and the edges consist of high frequency information. Edge Detection Error Rate (P_e) is a measure of probability of error in edge detection algorithm.

Probabilistic Rand Index (PRI) is used to measure the segmentation performance of WCE images. It counts the fraction of pairs of pixels whose labeling are consistent between the computed segmentation and the ground truth. It measures the similarity between the two partitions of the segmented images. Boundary Displacement Error (BDE) measures the average displacement error of boundary pixels between two segmented images. The Global Consistency Error (GCE) measures the extent to which one segmentation can be viewed as a refinement of the other. The Variation of Information (VOI) metric defines the distance between two segmentations as the average conditional entropy of one segmentation values given the other, and thus it measures the amount of randomness in segmentation which cannot be explained by the other.

Accuracy is the ratio of number of correct predictions to the total number of input samples. Sensitivity and specificity are the two statistical measures of the performance for binary classification test in medical field. Sensitivity measures the percentage of actual positives values which are correctly identified whereas specificity measures the percentage of negative values which are correctly identified.

True Positive Rate (TPR) corresponds to the proportion of positive data points that are correctly considered as positive, with respect to all positive data points. False Positive Rate (FPR) corresponds to the proportion of negative data points that are mistakenly considered as positive, with respect to all negative data points.

Precision measures the number of correct positive results divided by the number of positive results predicted by the classifier. It measures the amount of retrieved instances are relevant to the classification. It is also known as Positive Predicted Value (PPV).

Recall is the number of correct positive results divided by the number of all relevant samples. It measures the probability of relevant information were retrieved successfully among all the relevant instances.

Area under the Curve (AUC) is used in image classification analysis in order to determine which of the used models predicts the classes best. The performance of a classifier model is then calculated by calculating the AUC on Receiver Operating Characteristics (ROC). The AUC score will be between 0 and 1. The higher the value of AUC, usually the better the model is.FAR is the number of false positives that are expected to occur in the given number segments, or in a given entire image.

Dice Similarity Coefficient (DSC) is used to measure the performance of automatic segmentation of the bleeding regions in WCE against a manual segmentation. Jaccard coefficient is used for similarity and diversity measure of two sets of WCE images.

An image compression technique reduces the size of the images without degrading the quality of the images. Compression ratio (CR) measures the performances of the image compression techniques. The CR is defined as the ratio between the uncompressed size and compressed size.

Most of the classification problems handle imbalanced dataset. The balance between majority and minority class performance are measured through Geometric Mean or G-mean. The formulas of above measures are exposed in Table 1.

Table 2. Performance Measures

S.No	Performance Measure	Formula
1.	Mean Square Error (MSE)	MSE $=\frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y)-I'(x,y)]^2$ I(x,y) - Original image, I'(x,y) - Decompressed image M, N - Dimensions of the images
2.	Peak Signal to Noise Ratio (PSNR)	PSNR = $20 * \log_{10}(255/sqrt(MSE))$
3.	Root Mean Square Error (RMSE)	RMSE=$\sqrt{MSE}$
4.	Mean Absolute Error (MAE)	MAE $=\frac{1}{n}\sum_{j=1}^{n}\lvert y_j - \hat{y}_j\rvert$ N- Sample Size, y_j – Actual value, $\hat{y}_j$ – Predicted Value
5.	Information Fidelity	IF $= 1 - \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)-y(i,j))^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j))}$ where x(i, j) represents the original (reference) image and y(i, j) represents the distorted (modified) image.
6.	Structure similarity index map (SSIM)	SSIM(X,Y) $=\frac{(2\mu_x\mu_y+C_1)\times(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)\times(\sigma_x^2+\sigma_y^2+C_2)}$, X , Y – Two WCE Images μ_x, μ_y - Mean value of the two images σ_x, σ_y- Standard Deviation of two images, C_1, C_2 – Constant
7.	Image Enhancement Factor (IEF)	IEF $=\frac{\left(\sum_i\sum_j(n_{ij}-r_{ij})^2\right)}{\left(\sum_i\sum_j(x_{ij}-r_{ij})^2\right)}$, r_{ij} – Original Image, n_{ij} - Corrupted Image, x_{ij} - Restored Image,M x N - The size of the processed image
8.	Accuracy	(TP+TN) / (TP+FP+FN+TN)
9.	Sensitivity	TP / (TP + FN)
10.	Specificity	TN / (FP + TN)
11.	AUC	AUC $=\frac{\sum Rank(+)-\lvert+\rvert\times(\lvert+\rvert+1)/2}{\lvert+\rvert\lvert-\rvert}$ Where $\sum Rank(+)$is the ranks of all positively classified samples |+| is the number of positive examples in the dataset | - | is the number of negative examples in the dataset
12.	Precision	TP / (TP+FP)
13.	Recall	TP / (TP+FN)
14.	Geometric Mean	GMean = $\sqrt{(Sensitivity \times Specificity)}$
15. *	FAR (False Alarm Rate)	FAR = FP / (TP+TN+FP+FN), TP – True Positive, FP – False Positive, TN – True Negative, FN – False Negative
16.	MDR (Missed Detection Rate)	MDR = FN / (TP+TN+FP+FN)
17.	FPR	FP / (FP + TN)
18.	FNR	FN / (TP + FN)
19.	Dice Similarity Coefficient	DSC = 2TP / (2TP + FP +FN)
20.	Jaccard Index	$d = 1 - \frac{2\lvert X \cap Y\rvert}{\lvert X\rvert + \lvert y\rvert}$ where $\lvert X\rvert$ and $\lvert Y\rvert$ are the measure of elements of the set
21.	Compression Ratio	Compression Ratio = Original Image Size / Compressed Image Size

IV. CONCLUSION

WCE is a non-invasive technology that enables the physicians to observe the interior part of the small intestine. A major overhead associated with this technology is the large amount of time required to examine entire images and videos manually by physicians. This paper portrays several approaches used for analyzing the WCE images to extract the important features that are useful to classify the images as well as lead toward diagnostic decisions. This paper also discussed the issues related with pre-processing, feature extraction and classification of WCE images. Early diagnosis of inflammatory bowl diseases is a major prerequisite in order

to decrease the mortality rates. The CAD schemes aid the physicians for early disease diagnoses in GI tract, and hence improve the treatment therapies and thereby achieve higher degrees of positive outcomes within a short period of time. There is a need for automatic GI pathology identification, since the existing computational approaches does not provide a complete solution for all the problems related to the diagnosis of WCE images. This study can facilitate the researchers to contribute efficient CAD approaches for quick and accurate diagnosis of WCE images for the Physicians.

V. REFERENCES

[1] Chen, Y., & Lee, J. (2012). A Review of Machine-Vision-Based Analysis of Wireless Capsule Endoscopy Video. Diagnostic and Therapeutic Endoscopy, 2012;1155;1-9..

[2] Wu, X., Chen, H., Gan, T., Chen, J., Ngo, C., & Peng, Q. (2016). Automatic Hookworm Detection in Wireless Capsule Endoscopy Images. IEEE Transactions on Medical Imaging,2016;35(7);1741-1752.

[3] By Max Tilson, M.D. and John R. Saltzman, M.D. Brigham and Women's Hospital Harvard Medical School, Boston, MA, Small Bowel Bleeding and Capsule Endoscopy

[4] T. Yamada, D. H. Alpers, and C. Owyang, Textbook of gastroenterology: Wiley-Blackwell, 2009.

[5] Alam, M. W., Hasan, M. M., Mohammed, S. K., Deeba, F., & Wahid, K. A. (2017). Are Current Advances of Compression Algorithms for Capsule Endoscopy Enough? A Technical Review. IEEE Reviews in Biomedical Engineering, 2017;10;1109;26-43.

[6] Mateen, H., Basar, R., Ahmed, A. U., & Ahmad, M. Y. (2017). Localization of Wireless Capsule Endoscope: A Systematic Review. IEEE Sensors Journal, 2016;17(5);1109;1197.

[7] Hariton Costin (2014). Recent trends in Medical Image Processing Editorial (Preface) for a special issue of Computer Science Journal of Moldova 2014.

[8] Navnish Goel, Akhilendra Yadav, Brij Mohan Singh (2016), Medical Image Processing: A Review. Innovative Applications of Computational Intelligence on Power,

[9] Energy and Controls with their Impact on Humanit, IEEE 2016/.

[10] Yu Cao, Danyu Liu, Tavanapong, W., Wong, J., Jung Hwan Oh, & De Groen, P. (2007). Computer-Aided Detection of Diagnostic and Therapeutic Operations in Colonoscopy Videos. IEEE Transactions on Biomedical Engineering, 2007;54(7);1109;1268-1279..

[11] Gloger, O., Lehnert, B., Schrade, A., & Volzke, H. (2015). Fully Automated Glottis Segmentation in Endoscopic Videos Using Local Color and Shape Features of Glottal Regions. IEEE Transactions on Biomedical Engineering, 2015;62(3);1109;795-806..

[12] Pavankumar Naik, Arun Kumbi, Vishwanath Hiregoudar (2017). Wider Necessity of Digital Image processing in Biomedical with its further scope. International Journal for Research Trends and Innovation. Volume 1, Issue 2 2017..

[13] Halalli, B., & Makandar, A. (2018). Computer Aided Diagnosis - Medical Image Analysis Techniques. Breast Imaging 2018;10;5772.

[14] Kodogiannis, V., Boulougoura, M., Lygouras, J., & Petrounias, I. (2007). A neuro-fuzzy-based system for detecting abnormal patterns in wireless-capsule endoscopic images. Neurocomputing, 2006;70(4-6);704-717.

[15] LI, B., & MENG, M. Q. (2007). DISEASES DETECTION IN WIRELESS CAPSULE ENDOSCOPY IMAGES WITH COLOR FEATURE. International Journal of Information Acquisition, 2007;04(03);251-259.

[16] Smith, W., Vakil, N., & Maislin, S. (1992). Correction of distortion in endoscope images. IEEE Transactions on Medical Imaging, 1992;11(1),117-122.

[17] Vijayan Asari, K., Kumar, S., & Radhakrishnan, D. (1999). A new approach for nonlinear distortion correction in endoscopic images based on least squares estimation. IEEE Transactions on Medical Imaging, 1999;18(4);1109;42;345-354.

[18] Taosong He, Lichan Hong, Dongqing Chen, & Zhengrong Liang. (2001). Reliable path for virtual endoscopy: ensuring complete examination of human organs. IEEE Transactions on Visualization and Computer Graphics, 2001;7(4);1109;333-342..

[19] Helferty, J., Chao Zhang, McLennan, G., & Higgins, W. (2001). Videoendoscopic distortion correction and its application to virtual guidance of endoscopy. IEEE Transactions on Medical Imaging, 2001;20(7);1109;605-617.

[20] Li, B., & Meng, M. Q. (2006). Wireless Capsule Endoscopy Images Enhancement by Tensor Based Diffusion. 2006 International Conference of the IEEE Engineering in Medicine and Biology Society.2006;10;1109.

[21] P. Perona and J.Malik, "Scale-space and edge detection using anisotropic diffusion," IEEE Tansactions on PAMI 1990; 12; 629-639.

[22] Li, B., & Meng, M. Q. (2007). Analysis of the gastrointestinal status from wireless capsule endoscopy images using local color feature. 2007 International Conference on Information Acquisition.2007;10;1109.

[23] Li, B., & Meng, M. Q. (2007). Wireless Capsule Endoscopy Images Enhancement using Contrast Driven Forward and Backward Anisotropic Diffusion. 2007 IEEE International Conference on Image Processing. 2007;10;1109.

[24] G. Gilboa, N. Sochen, and Y.Y.Zeevi, "Forward-and-Backward diffusion processes for adaptive image enhancement and denoising," IEEE Transactions on Image Processing, 2002;11;689-703.

[25] K. Zuiderveld, "Contrast Limited Adaptive Histogram Equalization," Chapter VIII.5, Graphics Gems IV. P.S. Heckbert (Eds.), Cambridge, MA, Academic Press, 1994;474–485.

[26] Tsevas, S., Iakovidis, D. K., Maroulis, D., & Pavlakis, E. (2008). Automatic frame reduction of Wireless Capsule Endoscopy video. 2008 8th IEEE International Conference on BioInformatics and BioEngineering.2008;10;1109.

[27] Alexandre, L., Nobre, N., & Casteleiro, J. (2008). Color and Position versus Texture Features for Endoscopic Polyp Detection. 2008 International Conference on BioMedical Engineering and Informatics.2008;10;1109;246.

[28] T. Ojala and M. Pietikainen. Unsupervised texture segmentation using feature distributions. Pattern Recognition,1999;32:477–486.

[29] D. K. Iakovidis, D. E. Maroulis, S. A. Karkanis, and A. Brokos. A comparative study of texture features for the discrimination of gastric polyps in endoscopic video. In 18th IEEE Symposium on Computer-Based Medical Systems (CBMS'05), 2005;575–580.

[30] S. Karkanis, D. Iakovidis, D. Maroulis, D. Karras, and M. Tzivras. Computer-aided tumor detection in endoscopic video using color wavelet features. IEEE Trans. on Irformation Technology in Biomedicine,2003;7(3):141–152.

[31] Khun, P. C., Zhang Zhuo, Liang Zi Yang, Li Liyuan, & Liu Jiang. (2009). Feature selection and classification for Wireless Capsule Endoscopic frames. 2009 International Conference on Biomedical and Pharmaceutical Engineering. 2009;10;1109;5384106.

[32] Jung Hwan Oh, Sae Hwang, Yu Cao, Tavanapong, W., Danyu Liu, Wong, J., & De Groen, P. (2009). Measuring Objective Quality of Colonoscopy. IEEE Transactions on Biomedical Engineering, 2008;56(9),2190-2196.

[33] Li Liu, Chao Hu, Wentao Cai, & Meng, M. (2009). Capsule endoscope localization based on computer vision technique. 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2009;10.1109.

[34] B. Penna, T. Tillo, M. Grangetto, E. Magli and G. Olmo, "A technique for blood detection in wireless capsule endoscopy images," 2009 17th European Signal Processing Conference, Glasgow, 2009; 1864-1868.

[35] Sousa, A., Dinis-Ribeiro, M., Areia, M., & Coimbra, M. (2009). Identifying cancer regions in vital-stained magnification endoscopy images using adapted color histograms. 2009 16th IEEE International Conference on Image Processing (ICIP). 2009;10.1109.

[36] Häfner, M., Brunauer, L., Payer, H., Resch, R., Gangl, A., Uhl, A. Vécsei, A. (2010). Computer-Aided Classification of Zoom-Endoscopical Images Using Fourier Filters. IEEE Transactions on Information Technology in Biomedicine, 2010;14(4), 958-970.

[37] S. Kato, T. Fujii, I. Koba, Y. Sano, K. Fu, A. Parra-Blanco, H. Tajiri, S. Yoshida, and B. Rembacken, "Assessment of colorectal lesions using magnifiying colonoscopy and mucosal dye spraying: Can significant lesions be distinguished?" Endoscopy, 2001;33, 306–310.

[38] D. P. Hurlstone, S. S. Cross, I. Adam, A. J. Shorthouse, S. Brown, D. S. Sanders, and A. J. Lobo, "Efficacy of high magnification chromoscopic colonoscopy for the diagnosis of neoplasia in flat and depressed lesions of the colorectum: A prospective analysis," Gut, 2004;53; 2;284–290.

[39] Yi Wang, Tavanapong, W., Wong, J., JungHwan Oh, & De Groen, P. (2010). Detection of Quality Visualization of Appendiceal Orifices Using Local Edge Cross-Section Profile Features and Near Pause Detection. IEEE Transactions on Biomedical Engineering, 2009;57(3);685-695.

[40] Charisis, V., Hadjileontiadis, L. J., Liatsos, C. N., Mavrogiannis, C. C., & Sergiadis, G. D. (2010). Abnormal pattern detection in Wireless Capsule Endoscopy images using nonlinear analysis in RGB color space. 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology. 2010;10;1109.

[41] Vilarino, F., Spyridonos, P., DeIorio, F., Vitria, J., Azpiroz, F., & Radeva, P. (2010). Intestinal Motility Assessment With Video Capsule Endoscopy: Automatic Annotation of Phasic Intestinal Contractions. IEEE Transactions on Medical Imaging, 2010;29(2), 246-259.

[42] Khan, T. (2011). Low-complexity colour-space for capsule endoscopy image compression. Electronics Letters, 2011;47(22), 1217.

[43] Karargyris, A., & Bourbakis, N. (2011). Detection of Small Bowel Polyps and Ulcers in Wireless Capsule Endoscopy Videos. IEEE Transactions on Biomedical Engineering, 2011;58(10), 2777-2786.

[44] Behrens, A., Bommes, M., Gross, S., & Aach, T. (2011). Image quality assessment of endoscopic panorama images. 2011 18th IEEE International Conference on Image Processing. 2011;10;1109.

[45] Yao Shen, Guturu, P., & Buckles, B. P. (2012). Wireless Capsule Endoscopy Video Segmentation Using an Unsupervised Learning Approach Based on Probabilistic Latent Semantic Analysis with Scale Invariant Features. IEEE Transactions on Information Technology in Biomedicine, 2011;16(1);98-105.

[46] Kumar, R., Qian Zhao, Seshamani, S., Mullin, G., Hager, G., & Dassopoulos, T. (2012). Assessment of Crohn's Disease Lesions in Wireless Capsule Endoscopy Images. IEEE Transactions on Biomedical Engineering, 2011;59(2);355-362.

[47] Segui, S., Drozdzal, M., Vilarino, F., Malagelada, C., Azpiroz, F., Radeva, P., & Vitria, J. (2012). Categorization and Segmentation of Intestinal Content Frames for Wireless Capsule Endoscopy. IEEE Transactions on Information Technology in Biomedicine, 2012;16(6); 1341-1352.

[48] Baopu Li, & Meng, M. Q. (2012). Tumor Recognition in Wireless Capsule Endoscopy Images Using Textural Features and SVM-Based Feature Selection. IEEE Transactions on Information Technology in Biomedicine, 2012;16(3),323-329.

[49] Riaz, F., Silva, F. B., Ribeiro, M. D., & Coimbra, M. T. (2012). Invariant Gabor Texture Descriptors for Classification of Gastroenterology Images. IEEE Transactions on Biomedical Engineering, 2012;59(10);2893-2904.

[50] Puerto-Souza, G. A., & Mariottini, G. (2013). A Fast and Accurate Feature-Matching Algorithm for Minimally-Invasive Endoscopic Images. IEEE Transactions on Medical Imaging, 2013;32(7); 1201-1214.

[51] Charisis, V. S., Katsimerou, C., Hadjileontiadis, L. J., Liatsos, C. N., & Sergiadis, G. D. (2013). Computer-aided capsule endoscopy images evaluation based on color rotation and texture features: An educational tool to physicians. Proceedings of the 26th IEEE International Symposium on Computer-Based Medical Systems. 2013;10;1109.

[52] Eid, A., Charisis, V. S., Hadjileontiadis, L. J., & Sergiadis, G. D. (2013). A curvelet-based lacunarity approach for ulcer detection from Wireless Capsule Endoscopy images. Proceedings of the 26th IEEE International Symposium on Computer-Based Medical Systems. 2013;10;1109.

[53] Sainju, S., Bui, F. M., & Wahid, K. (2013). Bleeding detection in wireless capsule endoscopy based on color features from histogram probability. 2013 26th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE). 2013;10;1109.

[54] Riaz, F., Silva, F. B., Ribeiro, M. D., & Coimbra, M. T. (2013). Impact of Visual Features on the Segmentation of Gastroenterology Images Using Normalized Cuts. IEEE Transactions on Biomedical Engineering, 2012;60(5);1191-1201.

[55] Mamonov, A. V., Figueiredo, I. N., Figueiredo, P. N., & Richard Tsai, Y. (2014). Automated Polyp Detection in Colon Capsule Endoscopy. IEEE Transactions on Medical Imaging, 2014;33(7);1488-1502.

[56] Fu, Y., Zhang, W., Mandal, M., & Meng, M. Q. (2014). Computer-Aided Bleeding Detection in WCE Video. IEEE Journal of Biomedical and Health Informatics, 2013;18(2); 636-642.

[57] J. Liu and X. Yuan, "Obscure bleeding detection in endoscopy images using support vector machines," Opt. Eng., 2009;10;289–299.

[58] B. Li and M. Meng, "Computer-aided detection of bleeding regions for capsule endoscopy images," IEEE Trans. Biomed. Eng., 2009;56;1032–1039.

[59] G. Pan, G. Yan, X. Qiu, and J. Cui, "Bleeding detection in wireless capsule endoscopy based on probabilistic neural network," J. Med. Syst., 2011;35;1477–1484.

[60] Brzeski, A. (2014). Color-based Detection of Bleeding in Endoscopic Images. International Journal of Innovative Research in Computer and Communication Engineering, 2014;9;5606 – 5610.

[61] Vu, H., Echigo, T., Imura, Y., Yanagawa, Y., & Yagi, Y. (2014). Segmenting Reddish Lesions in Capsule Endoscopy Images Using a Gastrointestinal Color Space. 2014 22nd International Conference on Pattern Recognition. 2014;10;1109.

[62] Shanmuga sundaram, P., & Santhiyakumari, N. (2014). Interactive Segmentation of Capsule Endoscopy Images Using Grow Cut Method. 2014 International Conference on Computational Intelligence and Communication Networks. 2014;10;1109.

[63] Shahri, R., Arianti, D., Baharun, S., Islam, A. M., & Komaki, S. (2014). Pre-processing technique based on discrete cosine transform (DCT) and anisotropic contrast diffusion for wireless capsule endoscopy images. 2014 IEEE Conference on Biomedical Engineering and Sciences (IECBES). 2014;10;1109.

[64] B. Li, Max Q.-H. Meng,, "contrast diffusion", J. Vis. Commun. Image R. 2012;23;222–228.

[65] Hiroyasu, T., Hayashinuma, K., Ichikawa, H., Yagi, N., & Yamamoto, U. (2014). Endoscope image analysis method for evaluating the extent of early gastric cancer. 2014 IEEE Symposium on Computational Intelligence for Multimedia, Signal and Vision Processing (CIMSIVP). 2014;10;1109.

[66] Segui, S., Drozdzal, M., Zaytseva, E., Malagelada, C., Azpiroz, F., Radeva, P., & Vitria, J. (2014). Segui, S., Drozdzal, M., Zaytseva, E., Malagelada, C., Azpiroz, F., Radeva, P., & Vitria, J. (2014). Detection of Wrinkle Frames in Endoluminal Videos Using Betweenness Centrality Measures for Images. IEEE Journal of Biomedical and Health Informatics, 2014;18(6);1831-1838.

[67] Lin, B., Sun, Y., Sanchez, J. E., & Qian, X. (2015). Efficient Vessel Feature Detection for Endoscopic Image Analysis. IEEE Transactions on Biomedical Engineering, 2015;62(4);1141-1150.

[68] B. Lin, Y. Sun, J. Sanchez, and X. Qian, "Vesselness based feature extraction for endoscopic image analysis," in Proc. Int. Symp. Biomed. Imag., 2014;1295–1298.

[69] S. Giannarou, M. Visentini Scarzanella, and G.-Z. Yang, "Probabilistic tracking of affine-invariant anisotropic regions," IEEE Trans. Pattern Anal. Mach. Intell., 2013;35;130–143.

[70] K. Mikolajczyk and C. Schmid, "Scale & affine invariant interest point detectors," Int. J. Comput. Vis., 2004;60;63–86.

[71] K. Mikolajczyk, T. Tuytelaars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir, and L. J. V. Gool, "A comparison of affine region detectors," Int. J. of Comput. Vis., 2005; 65;43–72.

[72] D. Baboiu and G. Hamarneh, "Vascular bifurcation detection in scalespace," in IEEE Workshop Math. Meth. Biomed. Image Analysis, 2012;41–46.

[73] E. Rosten, R. Porter, and T. Drummond, "Faster and better: A machine learning approach to corner detection," IEEE Trans. Pattern Anal. Mach. Intell., 2010;32;105–119.

[74] M. Sofka and C. V. Stewart, "Retinal vessel centerline extraction using multiscale matched filters, confidence and edge measures," IEEE Trans. Med. Imag., 2006;25;1531–1546.

[75] Wang, D., Xie, X., Li, G., Yin, Z., & Wang, Z. (2015). A Lumen Detection-Based Intestinal Direction Vector Acquisition Method for Wireless Endoscopy Systems. IEEE Transactions on Biomedical Engineering, 2015;62(3),807-819.

[76] G. Gallo and A. Torrisi, "Lumen detection in endoscopic images: A boosting classification approach," Int. J. Adv. Intell. Syst.,2012;5;127–134.

[77] X. Zabulis, A. A. Argyros, and D. P. Tsakiris, "Lumen detection for capsule endoscopy," in Proc. IEEE Int. Conf. Intell. Robots Syst., 2008;3921–3926.

[78] Ghosh, T., Fattah, S. A., Bashar, S. K., Shahnaz, C., Wahid, K. A., Zhu, W., & Ahmad, M. O. (2015). An automatic bleeding detection technique in wireless capsule endoscopy from region of interest. 2015 IEEE International Conference on Digital Signal Processing (DSP). 2015;10;1109.

[79] T. Ghosh, K. Wahid, and S. A. Fattah, "Automatic Bleeding Detection in Wireless Capsule Endoscopy Based on RGB Pixel Intensity Ratio", in Proc. iCEEiCT, 2014;1-4.

[80] T. Ghosh, S. K. Bashar, M. S. Alam, K. Wahid, and S. A. Fattah, "A Statistical Feature Based Novel Method to Detect Bleeding in Wireless Capsule Endoscopy Images", in Proc. ICIEV,2014;1-4.

[81] L. Baopu and M. Q. H. Meng, "Computer-Aided Detection of Bleeding Regions for Capsule Endoscopy Images," IEEE Trans. Biomedical Engineering, 2009;56;1032-39.

[82] Bae, S., & Yoon, K. (2015). Polyp Detection via Imbalanced Learning and Discriminative Feature Learning. IEEE Transactions on Medical Imaging, 2015;34(11);2379-2393.

[83] Yuan, Y., Wang, J., Li, B., & Meng, M. Q. (2015). Saliency Based Ulcer Detection for Wireless Capsule Endoscopy Diagnosis. IEEE Transactions on Medical Imaging, 2015;34(10); 2046-2057.

[84] B. Li and M. Q.-H. Meng, "Texture analysis for ulcer detection in capsule endoscopy images," Image Vis. Comput., 2009;27;1336–1342.

[85] V. S. Charisis, C. Katsimerou, L. J. Hadjileontiadis, C. N. Liatsos, and G. D. Sergiadis, "Computer-aided capsule endoscopy images evaluation based on color rotation and texture features: An educational tool to physicians," in Proc. IEEE 26th Int. Symp. Comput.-Based Med. Syst., 2013;203–208.

[86] L. Yu, P. C. Yuen, and J. Lai, "Ulcer detection in wireless capsule endoscopy images," in Proc. 21st Int. Conf. IEEE Pattern Recognit., 2012;45–48.

[87] Yuan, Y., Li, B., & Meng, M. Q. (2016). Bleeding Frame and Region Detection in the Wireless Capsule Endoscopy Video. IEEE Journal of Biomedical and Health Informatics, 2015;20(2); 624-630.

[88] L. Cui, C. Hu, Y. Zou, and M.-H. Meng, "Bleeding detection in wireless capsule endoscopy images by support vector classifier," in Information and Automation (ICIA), 2010 IEEE International Conference on, 2010;1746-1751.

[89] G. Lv, G. Yan, and Z. Wang, "Bleeding detection in wireless capsule endoscopy images based on color invariants and spatial pyramids using support vector machines," in Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE, 2011;6643-6646.

[90] J. Yang, K. Yu, Y. Gong, and T. Huang, "Linear spatial pyramid matching using sparse coding for image classification," in Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, 2009;1794-1801.

[91] J. Wang, J. Yang, K. Yu, F. Lv, T. Huang, and Y. Gong, "Locality-constrained linear coding for image classification," in Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on, 2010;3360-3367.

[92] Reeha K. R., Shailaja K., & Gopi, V. P. (2016). Undecimated Complex Wavelet Transform based bleeding detection for endoscopic images. 2016 Second International Conference on Cognitive Computing and Information Processing (CCIP). 2016;10;1109.

[93] Wang, S., Cong, Y., Fan, H., Liu, L., Li, X., Yang, Y., Yu, H. (2016). Computer-Aided Endoscopic Diagnosis

Without Human-Specific Labeling. IEEE Transactions on Biomedical Engineering, 2016;63(11);2347-2358.

[94] W.-J. Li and D.-Y. Yeung, "Mild: Multiple-instance learning via disambiguation," IEEE Trans. Knowl. Data Eng., 2010;22;76–89.

[95] Huang, C., Chen, Y., Chen, W., Cheng, H., & Sheu, B. (2016). Gastroesophageal Reflux Disease Diagnosis Using Hierarchical Heterogeneous Descriptor Fusion Support Vector Machine. IEEE Transactions on Biomedical Engineering, 2016;63(3);588-599.

[96] X. Wu, H. Chen, T. Gan, J. Chen, C. Ngo and Q. Peng, "Automatic Hookworm Detection in Wireless Capsule Endoscopy Images," in IEEE Transactions on Medical Imaging, 2016;35;1741-1752.

[97] Shrestha, R., Mohammed, S. K., Hasan, M. M., Zhang, X., & Wahid, K. A. (2016). Automated Adaptive Brightness in Wireless Capsule Endoscopy Using Image Segmentation and Sigmoid Function. IEEE Transactions on Biomedical Circuits and Systems, 2016;10(4); 884-892.

[98] ZHOU, S., CHEN, S., Karim, A., BAI, J., & FAN, C. (2017). Bleeding Detection in Wireless Capsule Endoscope Based on Color Feature Vector. DEStech Transactions on Computer Science and Engineering, (aice-ncs).2016;10;12783.

[99] Zhou S., Song X., Siddique M.A., et al. Bleeding detection in wireless capsule endoscopy images based on binary feature vector, Intelligent Control and Information Processing (ICICIP), 2014 Fifth International Conference on. IEEE, 2014;29-33.

[100] Mathew M., Gopi V.P. Transform based bleeding detection technique for endoscopic images, Electronics and Communication Systems (ICECS), 2015 2nd International Conference on. IEEE, 2015;1730-1734.

[101] Kundu, A. K., Bhattacharjee, A., Fattah, S. A., & Shahnaz, C. (2016). Automatic ulcer detection scheme using gray scale histogram from wireless capsule endoscopy. 2016 IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE). 2016;10;1109.

[102] S. T. Jadhav and S. H. Dabhole, "An optimal imf selection based on fast beemd with dlac analysis for detection of polyp and ulcer in wce images," in Proc. International Conference on Electronics and Communication Systems, 2015;264–270.

[103] Karargyris and N. Bourbakis, "Identification of ulcers in wireless capsule endoscopy videos," in Proc. IEEE International Symposium on Biomedical Imaging: From Nano to Macro, 2009,;554–557.

[104] Shahril, R., Baharun, S., & Islam, A. M. (2016). Pre-processing Technique for Wireless Capsule Endoscopy Image Enhancement. International Journal of Electrical and Computer Engineering (IJECE), 2016;6(4); 1617.

[105] Yuan, Y., Li, B., & Meng, M. Q. (2016). Improved Bag of Feature for Automatic Polyp Detection in Wireless Capsule Endoscopy Images. IEEE Transactions on Automation Science and Engineering, 2015;13(2),529-535.

[106] Barbalata, C., & Mattos, L. S. (2016). Laryngeal Tumor Detection and Classification in Endoscopic Video. IEEE Journal of Biomedical and Health Informatics, 2014;20(1); 322-332.

[107] M. Hirota, T. Tamaki, K. Kaneda, S. Yosida, and S. Tanaka, "Feature extraction from images of endoscopic large intestine," Inst. Electron. Eng. Korea, Seoul, Korea, 2008; 100–105.

[108] F. Rossant, M. Badellino, A. Chavillon, I. Bloch, and M. Paques, "A morphological approach for vessel segmentation in eye fundus images, with quantitative evaluation," J. Med. Imag. Health Informat., 2011;42–49.

[109] Bernal, J., Tajkbaksh, N., Sanchez, F. J., Matuszewski, B. J., Chen, H., Yu, L., Histace, A. (2017). Comparative Validation of Polyp Detection Methods in Video Colonoscopy: Results From the MICCAI 2015 Endoscopic Vision Challenge. IEEE Transactions on Medical Imaging, 36(6), 1231-1249. doi:10.1109/tmi.2017.2664042

[110] Riaz, F., Hassan, A., Nisar, R., Dinis-Ribeiro, M., & Coimbra, M. T. (2017). Content-Adaptive Region-Based Color Texture Descriptors for Medical Images. IEEE Journal of Biomedical and Health Informatics, 21(1), 162-171. doi:10.1109/jbhi.2015.2492464

[111] F. Riaz, A. Hassan, S. Rehman, and U. Qamar, "Texture classification using rotation- and scale-invariant gabor texture features," Signal Processing Letters, IEEE, vol. 20, no. 6, pp. 607–610, 2013.

[112] F. Riaz, "Assisted analysis of gastroenterology images using computer vision methodologies," Phd Thesis, Faculdade de Ciencias da Universidade do Porto, 2012

[113] F. Riaz, M. Dinis-Ribeiro, P. Pimentel-Nunes, and M. T. Coimbra, "A dft based rotation and scale invariant gabor texture descriptor and its application to gastroenterology.," in ICIP, 2013;1443–1446.

[114] T. Ojala, M. Pietikainen, and T. M ¨ aenp ¨ a¨a, "Multiresolution gray-scale ¨ and rotation invariant texture classification with local binary patterns," Pattern Analysis and Machine Intelligence, IEEE Transactions on,2002;24;971–987.

[115] M. Cimpoi, S. Maji, I. Kokkinos, S. Mohamed, and A. Vedaldi, "Describing textures in the wild," in Computer Vision and Pattern Recognition (CVPR), 2014 IEEE Conference on, 2014;3606–3613.

[116] Yuan, Y., Li, B., & Meng, M. Q. (2017). WCE Abnormality Detection Based on Saliency and Adaptive Locality-Constrained Linear Coding. IEEE Transactions on Automation Science and Engineering, 2016;14(1);149-159.

[117] G. Csurka, C. R. Dance, L. Fan, J. Willamowski, and C. Bray, "Visual categorization with bags of keypoints," in Proc. Workshop Statist. Learn. Comput. Vis. (ECCV), Prague, Czech Republic, 2004;1–22.

[118] J. Yang, K. Yu, Y. Gong, and T. Huang, "Linear spatial pyramid matching using sparse coding for image classification," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., 2009; 1794–1801.

[119] Souaidi, M., Abdelouahad, A. A., & Ansari, M. E. (2017). A fully automated ulcer detection system for wireless capsule endoscopy images. 2017 International Conference on Advanced Technologies for Signal and Image Processing (ATSIP). 2017;10;1109.

[120] Perperidis, A., Akram, A., Altmann, Y., McCool, P., Westerfeld, J., Wilson, D., McLaughlin, S. (2017). Automated Detection of Uninformative Frames in Pulmonary Optical Endomicroscopy. IEEE Transactions on Biomedical Engineering, 2016;64(1); 87-98.

[121] Deeba, F., Mohammed, S. K., Bui, F. M., & Wahid, K. A. (2017). Efficacy Evaluation of SAVE for the Diagnosis of Superficial Neoplastic Lesion. IEEE Journal of Translational Engineering in Health and Medicine, 5, 2017;10;1109;1-12.

[122] Figueiredo, I. N., Leal, C., Pinto, L., Figueiredo, P. N., & Tsai, R. (2017). Dissimilarity Measure of Consecutive Frames in Wireless Capsule Endoscopy Videos: A Way of Searching for Abnormalities. 2017 IEEE 30th International Symposium on Computer-Based Medical Systems (CBMS). 2017;10;1109.

[123] Charisis, V. S., & Hadjileontiadis, L. J. (2016). Use of adaptive hybrid filtering process in Crohn's disease lesion detection from real capsule endoscopy videos. Healthcare Technology Letters, 2015;3(1);27-33.

[124] Ghosh, T., Fattah, S. A., & Wahid, K. A. (2018). CHOBS: Color Histogram of Block Statistics for Automatic Bleeding Detection in Wireless Capsule Endoscopy Video. IEEE Journal of Translational Engineering in Health and Medicine, 6, 2018;10;1109;1-12.

[125] Rajaeefar, Atefe & Emami, Ali & Soroushmehr, S.M.Reza & Karimi, Nader & Samavi, Shadrokh & Najarian, Kayvan. (2018). Lossless Image Compression Algorithm for Wireless Capsule Endoscopy by Content-Based Classification of Image Blocks 2018.

[126] Mohammed, A., Farup, I., Pedersen, M., Hovde, Ø., & Yildirim, S. (2018). Stochastic Capsule Endoscopy Image Enhancement. 2018;10;20944..

[127] Fattal, R.; Agrawala, M.; Rusinkiewicz, S. Multiscale shape and detail enhancement from multi-light image collections. ACM Trans. Graph. 2007;26, 51

[128] Farbman, Z.; Fattal, R.; Lischinski, D.; Szeliski, R. Edge-preserving decompositions for multi-scale tone and detail manipulation. ACM Trans. Graph. 2008;27, 67.

[129] Figueiredo, P., Figueiredo, I., Pinto, L., Kumar, S., Tsai, Y., & Mamonov, A. (2019). Polyp detection with computer-aided diagnosis in white light colonoscopy: comparison of three different methods. Endoscopy International Open, 02019;7(02);E209-E215.

[130] Bernal J, Sanchez FJ, Fernandez-Esparrach G et al. WM-DOVA maps for accurate polyp highlighting in colonoscopy: Validation vs. saliency maps from physicians. Comp Med Imaging Graphics 2015; 43: 99 – 111

[131] Hajabdollahi, Mohsen & Esfandiarpoor, Reza & Khadivi, Pejman & Soroushmehr, S.M.Reza & Karimi, Nader & Najarian, Kayvan & Samavi, Shadrokh. (2018). Segmentation of Bleeding Regions in Wireless Capsule Endoscopy for Detection of Informative Frames 2018.

[132] A. Koulaouzidis, "KID. Koulaouzidis-Iakovidis database for capsule endoscopy", 2016.

[133] F.Deeba, "Bleeding images and corresponding ground truth of CE images", 2016.

[134] Figueiredo, I. N., Leal, C., Pinto, L., Figueiredo, P. N., & Tsai, R. (2018). Hybrid multiscale affine and elastic image registration approach towards wireless capsule endoscope localization. Biomedical Signal Processing and Control, 2017;39;486-502.

[135] Long, M., Lan, Z., Xie, X., Li, G., & Wang, Z. (2018). Image Enhancement Method Based on Adaptive Fraction Gamma Transformation and Color Restoration for Wireless Capsule Endoscopy. 2018 IEEE Biomedical Circuits and Systems Conference (BioCAS). 2018;10;1109;

[136] Souaidi, M., Abdelouahed, A. A., & El Ansari, M. (2018). Multi-scale completed local binary patterns for ulcer detection in wireless capsule endoscopy images. Multimedia Tools and Applications. 2018;10;1007.

[137] Li B, Meng MQH, Lau JY (2011) Computer-aided small bowel tumor detection for capsule endoscopy. Artif Intell Med 2011;52(1);11–16.

[138] Bchir, O., Ben Ismail, M. M., & AlZahrani, N. (2018). Multiple bleeding detection in wireless capsule endoscopy. Signal, Image and Video Processing, 2018;13(1); 121-126.

[139] Vani, V., & Prashanth, K. V. (2018). Image Enhancement of Wireless Capsule Endoscopy Frames Using Image Fusion Technique. IETE Journal of Research, 2018;10;1-13.

[140] V. P. Gopi, P. Palanisamy, and S. I. Niwas, “Capsule endoscopic colour image denoising using complex wavelet transform,” In Wireless Networks and Computational Intelligence. Berlin: Springer, 2012;220–9.

[141] M. Moradi, A. Falahati, A. Shahbahrami, and R. Hassanpour, “Improving visual quality in wireless capsule endoscopy images with contrast-limited adaptive histogram equalization,” In 2nd International Conference on Pattern Recognition and Image Analysis (IPRIA), IEEE, 2015;1–5.

[142] T. H. Khan, S. K. Mohammed, M. S. Imtiaz, and K. A. Wahid, “Color reproduction and processing algorithm based on real-time mapping for endoscopic images,” Springer Plus, 2016;5;1-17.

[143] T. Welsh, M. Ashikhmin, and K. Mueller, “Transferring color to greyscale images,” ACM Trans Graph., 2002; 21;277–80.

[144] V. Korostyshevskiy, “Grayscale to RGB converter,” MATLAB Central File Exchange, 2006.

[145] H. Okuhata, H. Nakamura, S. Hara, H. Tsutsui, and T. Onoye, “Application of the real-time Retinex image enhancement for endoscopic images,” In 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2013;3407–10.

[146] F. Vogt, S. Krüger, H. Niemann, and C. Schick, “A system for real-time endoscopic image enhancement,” In International Conference on Medical Image Computing and Computer-Assisted Intervention, Springer, Berlin, Heidelberg, 2003;356–63.

[147] A. Mostafa, K. Wahid, and S. B. Ko, “An efficient YUV based image compression algorithm for wireless capsule endoscopy,” In 24th Canadian Conference on Electrical and Computer Engineering (CCECE), IEEE, 2011; 943–46.

[148] N. Sudha, and N. M. Santhiya Kumari, “Summarizing wireless capsule endoscopy video frame based on inter-frame structural similarity index,” Adv. Nat. Appl. Sci., 2016;10;199–208.

[149] Hajabdollahi, M., Esfandiarpoor, R., Soroushmehr, S.M., Karimi, N., Samavi, S.A., & Najarian, K. (2018). Segmentation of Bleeding Regions in Wireless Capsule Endoscopy Images an Approach for inside Capsule Video Summarization. CoRR, 2018;1802.07788.

[150] E. Tuba, M. Tuba and R. Jovanovic, “An algorithm for automated segmentation for bleeding detection in endoscopic images”, International Joint Conference on Neural Networks (IJCNN), 2017;4579-4586.

[151] F. Deeba, F.M. Bui and K.A. Wahid, “Automated growcut for segmentation of endoscopic images”, International Joint Conference on Neural Networks (IJCNN), 2016;4650-4657.

[152] Xing, X., Jia, X., & Meng, M. -. (2018). Bleeding Detection in Wireless Capsule Endoscopy Image Video Using Superpixel-Color Histogram and a Subspace KNN Classifier. 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).2018;10;1109.

[153] Coelho, P., Pereira, A., Leite, A., Salgado, M., & Cunha, A. (2018). A Deep Learning Approach for Red Lesions Detection in Video Capsule Endoscopies. Lecture Notes in Computer Science, 2018;10;1007;553-561.

[154] Sainju, S., Bui, F.M., Wahid, K.A.: Automated bleeding detection in capsule endoscopy videos using statistical features and region growing. J. Med. Syst. 2014;38(4);25. http://link.springer.com/10.1007/s10916-014-0025-1

[155] Figueiredo, I.N., Kumar, S., Leal, C., Figueiredo, P.N.: Computer-assisted bleeding detection in wireless capsule endoscopy images. Comput. Methods Biomech. Biomed. Eng. Imaging Vis. 2013;1(4);198–210. http://www.tandfonline.com/

[156] Usman, M.A., Satrya, G., Usman, M.R., Shin, S.Y.: 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

[157] Xiong, Y., Zhu, Y., Pang, Z., Ma, Y., Chen, D., Wang, X.: Bleeding detection in wireless capsule endoscopy based on MST clustering and SVM. In: IEEE Workshop on Signal Processing Systems (SiPS), 2015;35;1–4. http:// ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=7345001

[158] Vasilakakis, M. D., Iakovidis, D. K., Spyrou, E., & Koulaouzidis, A. (2018). DINOSARC: Color Features Based on Selective Aggregation of Chromatic Image Components for Wireless Capsule Endoscopy. Computational and Mathematical Methods in Medicine, 2018; 1-11.

[159] D. K. Iakovidis and A. Koulaouzidis, “Automatic lesion detection in wireless capsule endoscopy—a simple solution for a complex problem,” in Proceedings of IEEE International Conference on Image Processing (ICIP), Paris, France, 20142226–2240.

[160] G. Wyszecki and W. S. Stiles, Color Science, Wiley, Vol. 8, Wiley, New York, NY, USA, 1982

[161]Ghosh, T., Li, L., & Chakareski, J. (2018). Effective Deep Learning for Semantic Segmentation Based Bleeding Zone Detection in Capsule Endoscopy Images. 2018 25th IEEE International Conference on Image Processing (ICIP) 2018;10;1109.
[162]D. K. Iakovidis and A. Koulaouzidis, "Software for enhanced video capsule endoscopy: challenges for essential progress," Nature Reviews Gastroenterology & Hepatology, 2015;12;172–186.
[163]X. Jia and M. Q.-H. Meng, "A study on automated segmentation of blood regions in wireless capsule endoscopy images using fully convolutional networks," in 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017). IEEE, 2017;179–182.
[164]Varma Malathkara, N., & Soni, S. K. (2018). Low-Complexity and Lossless Image Compression Algorithm for Capsule Endoscopy. SSRN Electronic Journal. 2018;10;2139.
[165]Fan, S., Xu, L., Fan, Y., Wei, K., & Li, L. (2018). Computer-aided detection of small intestinal ulcer and erosion in wireless capsule endoscopy images. Physics in Medicine & Biology, 2018;63(16);165001.
[166]Aoki, T., Yamada, A., Aoyama, K., Saito, H., Tsuboi, A., Nakada, A., … Tada, T. (2019). Automatic detection of erosions and ulcerations in wireless capsule endoscopy images based on a deep convolutional neural network. Gastrointestinal Endoscopy, 2018;89(2);357-363.
[167]Kundu, A. K., Fattah, S. A., & Rizve, M. N. (2018). An Automatic Bleeding Frame and Region Detection Scheme for Wireless Capsule Endoscopy Videos Based on Interplane Intensity Variation Profile in Normalized RGB Color Space. Journal of Healthcare Engineering, 2018;1-12.
[168]T. Ghosh, S. A. Fattah, C. Shahnaz, and K. A. Wahid, "An automatic bleeding detection scheme in wireless capsule endoscopy based on histogram of an RGB-indexed image," in 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2014;4683–4686.
[169]Long, M., Li, Z., Xie, X., Li, G., & Wang, Z. (2018). Adaptive Image Enhancement Based on Guide Image and Fraction-Power Transformation for Wireless Capsule Endoscopy. IEEE Transactions on Biomedical Circuits and Systems, 2018;12(5); 993-1003.
[170]S. Huang, F. Cheng, Y. Chiu. "Efficient contrast enhancement using adaptive gamma correction with weighting distribution". IEEE Transactions on Image Processing, 2013;22(3);1032-1041.
[171]D. Sheet, H. Garud, A. Suveer, et al. "Brightness preserving dynamic fuzzy histogram equalization". IEEE Transactions on Consumer Electronics, 2010; 56(4); 2475-2480.
[172]G. Deng. "A generalized unsharp masking algorithm". IEEE transactions on Image Processing, 2011; 20(5); 1249-1261.
[173]X. Fu, D. Zeng, Y. Huang, X. Zhang, X. Ding. "A weighted variational model for simultaneous reflectance and illumination estimation", Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016; 2782-2790.
[174]Tuba, E., Tomic, S., Beko, M., Zivkovic, D., & Tuba, M. (2018). Bleeding Detection in Wireless Capsule Endoscopy Images Using Texture and Color Features. 2018 26th Telecommunications Forum (TELFOR).2018;10;1109.
[175]Sivakumar, P., & Kumar, B. M. (2018). A novel method to detect bleeding frame and region in wireless capsule endoscopy video. Cluster Computing. 2018;10;1007.
[176]JI, X., XU, T., & LI, W. (2018). A Recognition Algorithm for Wireless Capsule Gastroscopy Images. DEStech Transactions on Computer Science and Engineering, (iece). 2018;26638.
[177]D.J. Barbosa, J. Ramos, C.S. Lima, Detection of small bowel tumors in capsule endoscopy frames using texture analysis based on the discrete wavelet transform, in: Proc. of 30th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., 2008;1102-1105.
[178]J. Deng, L. Zhao, Image classification model with multiple feature selection and support vector machine, J. Jilin Univ. (Science Edition). 4 2016;862-866.
[179]Leenhardt, R., Vasseur, P., Li, C., Saurin, J. C., Rahmi, G., Cholet, F., Romain, O. (2019). A neural network algorithm for detection of GI angiectasia during small-bowel capsule endoscopy. Gastrointestinal Endoscopy, 2019;89(1);189-194.
[180]Shanmuga Sundaram, P., & Santhiyakumari, N. (2019). An Enhancement of Computer Aided Approach for Colon Cancer Detection in WCE Images Using ROI Based Color Histogram and SVM2. Journal of Medical Systems, 2019;43(2).
[181]Vijayakumar, V., Priyan, M. K., Ushadevi, G., Varatharajan, R., Manogaran, G., and Tarare, P. V., E-health cloud security using timing enabled proxy re-encryption. Mobile Networks and Applications: 2018;1–12.
[182]Mathan, K., Kumar, P. M., Panchatcharam, P., Manogaran, G., and Varadharajan, R., A novel Gini index decision tree data mining method with neural network classifiers for prediction of heart disease. Des. Autom. Embed. Syst.:2018;1–18.
[183]Wang, Q., Pan, N., Xiong, W., Lu, H., Li, N., & Zou, X. (2019). Reduction of bubble-like frames using a RSS filter in wireless capsule endoscopy video. Optics & Laser Technology, 2018;110;152-157.
[184]Sharma, R., Bhadu, R., Soni, S. K., & Varma, N. (2018). Reduction of Redundant Frames in Active Wireless Capsule Endoscopy. Lecture Notes in Electrical Engineering, 2018;1-7.
[185]C. Sampath Kannangara et al., "Low-complexity skip prediction for H.264 through lagrangian cost estimation," IEEE Trans. Circuits Syst. Video Technol., 2006;16;202–207.
[186]H. G. Lee, M. K. Choi, B. S. Shin, and S. C. Lee, "Reducing redundancy in wireless capsule endoscopy videos," Comput. Biol. Med., 2013;43; 670–682.
[187]C. Yi, L. Yihua, and R. Haozheng, "Trimming the wireless capsule endoscopic video by removing redundant frames," 2012 Int. Conf. Wirel. Commun. Netw. Mob. Comput. WiCOM 2012, 2012.
[188]Varma Malathkar, N., & Kumar Soni, S. (2019). Low complexity image compression algorithm based on hybrid DPCM for wireless capsule endoscopy. Biomedical Signal Processing and Control, 2019;48;197-204.
[189] X. Xiang, L. GuoLin, C. XinKai, L. Lu, Z. Chun, W. ZhiHua, A low power digital IC design inside the wireless endoscopy capsule, IEEE J. SolidState Circuits 41 2006; 2390–2400.http://dx.doi.org/10.1109/JSSC.2006.882884.
[190]X. Chen, X. Zhang, L. Zhang, N. Qi, H. Jiang, Z. Wang, A wireless capsule endoscope system with a low-power controlling and processing ASIC, IEEE Trans. Biomed. Circuits Syst. 3 2009; 11–22. http://dx.doi.org/10.1109/ TBCAS.2008.2006493.
[191]T.H. Khan, K.A. Wahid, Lossless and low-power image compressor for wireless capsule endoscopy, Vlsi Des. (2011), http://dx.doi.org/10.1155/2011/ 343787.
[192]T.H. Khan, K.A. Wahid, Design of a lossless image compression system for video capsule endoscopy and its performance in in-vivo trials, Sensors 14 2014; 20779–20799, http://dx.doi.org/10.3390/s141120779.
[193]S.K. Mohammed, K. Mafijur Rahman, K.A. Wahid, Lossless compression in bayer color filter array for capsule endoscopy, IEEE Access 5 2017;13823–13834. http://dx.doi.org/10.1109/ACCESS.2017.2726997.
[194]Sharif, M., Attique Khan, M., Rashid, M., Yasmin, M., Afza, F., & Tanik, U. J. (2019). Deep CNN and geometric features-based gastrointestinal tract diseases detection and classification from wireless capsule endoscopy images. Journal of Experimental & Theoretical Artificial Intelligence, 2019; 1-23.