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# Computer-aided Decision Support Systems for Endoscopy in the Gastrointestinal Tract: A Review

Michael Liedlgruber and Andreas Uhl

***Abstract*—Today, medical endoscopy is a widely used procedure to inspect the inner cavities of the human body. The advent of endoscopic imaging techniques – allowing the acquisition of images or videos – created the possibility for the development of the whole new branch of computer-aided decision support systems. Such systems aim at helping physicians to identify possibly malignant abnormalities more accurately. At the beginning of this work we give a brief introduction to the history of endoscopy, followed by introducing the main types of endoscopes which emerged so far (flexible endoscope, wireless capsule endoscope, and confocal laser endomicroscope). We then give a brief introduction to computer-aided decision support systems specifically targeted at endoscopy in the gastrointestinal tract. Then we present general facts and figures concerning computer-aided decision support systems and summarize work specifically targeted at computer-aided decision support in the gastrointestinal tract. This summary is followed by a discussion of some common issues concerning the approaches reviewed and suggestions of possible ways to resolve them.**

***Index Terms*—Endoscopy, Wireless Capsule Endoscopy, Confocal Laser Endomicroscopy, Gastrointestinal Tract, Computer-aided Decision Support**

## I. Introduction

SINCE medical endoscopy is a minimally invasive and relatively painless procedure, allowing to inspect the inner cavities of the human body, endoscopes play an important role in modern medicine. In medical practice different cavities within the body exist which are are regularly inspected with an endoscope [1], e.g. the lower respiratory tract (bronchoscopy), the urinary tract (cystoscopy), or the female reproductive system (gynoscopy). But there also exist procedures which are performed through small incisions to reach cavities which are normally closed, such as for the example the abdominal or pelvic cavity (laparoscopy) or organs of the chest (thorascopy). Another important field in medical endoscopy, which this survey focuses at, is the inspection of the gastrointestinal tract (GI tract).

Based on endoscopy of the GI tract, physicians are able to detect severe diseases already in early development stages and therefore the mortality rate for many diseases, especially different types of cancers, has been lowered drastically throughout the last years [1], [2]. Some examples of conditions which are known to be pre-malignant or to increase the risk of cancer in the GI tract are adenomas, Barrett's esophagus, Crohn's disease, celiac disease, and a Helicobacter pylori infection. But also the detection of GI bleeding, being a sign of malignancy, is important in gastrointestinal endoscopy.

The advent of endoscopes with the ability to take digital pictures created the whole new field of computer-aided decision support systems (CADSSs) in medical endoscopy. Such systems are designed to detect and/or classify abnormalities and thus assist a medical expert in improving the accuracy of medical diagnosis. In addition, different methods have emerged which do not directly provide decision-support. Instead they aim for example at enhancing image quality, detecting degraded images, or provide endoscope navigation support. Throughout this work we use the term "supportive systems" for such methods.

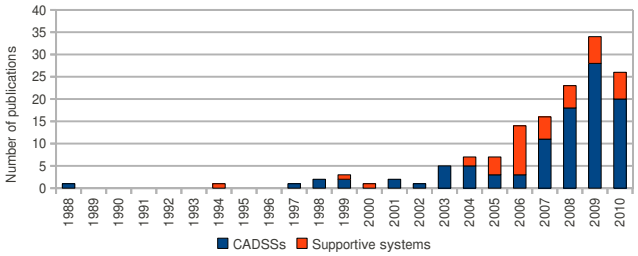


Figure 1. Number of publications between 1988 and 2010 found on PubMed and ScienceDirect when searching for publications aiming at supporting medical endoscopy in the GI tract (search was conducted on the 6th of June, 2011).

To highlight the relevance of CADSSs and supportive systems we conducted an exhaustive search for publications dealing with these topics (on PubMed [2] and on ScienceDirect [3]), which yielded the search results presented in Fig. 1. In order to find relevant publications our search was based on key terms corresponding to different endoscopic techniques and pathologies (the respective search queries can be found in [3]). The results show that there is a rising interest in this research topic, starting about one decade ago.

The remaining part of this work is structured as follows: Section II reviews the technological advances in endoscopy. We then discuss CADSSs in more detail in Section III. This discussion includes a brief overview of CADSS, general facts and figures, and a detailed review of proposed CADSSs found in literature. Problems inherent to CADSSs and possible ways to cope with them are discussed in Section IV. Section V concludes this work.

## II. Technological Advances in Endoscopy

Endoscopy, as we know it today, is performed using a flexible endoscope, sometimes also referred to as videoscope. This type of endoscope has been introduced in the mid 1960s. While the first endoscopes used fiber optics and an eyepiece lens to visualize the inner cavities of the human body, modern endoscopes are very compact devices, including a light source, and a CCD or CMOS chip for taking pictures. But the basic concept did not change very much since those days. In addition to the digital imaging chip, modern endoscopes contain a light source at the distal tip and are equipped with an accessory channel, which allows the entry of medical instruments to take tissue samples, perform cleansing of poorly prepared areas, perform polypectomies, and perform endoscopic resections without any invasive surgery involved. Depending on the region within the GI

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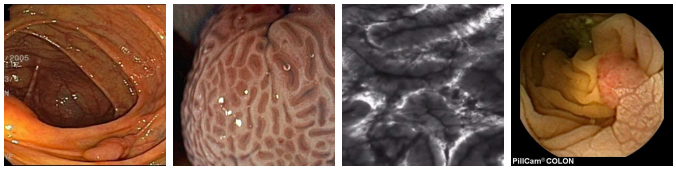
[1] See http://en.wikipedia.org/wiki/Endoscopy

[2] PubMed located at http://www.ncbi.nlm.nih.gov/pubmed

[3] ScienceDirect located at http://www.sciencedirect.com




(a) (b) (c) (d)

Figure 2. Sample images showing a colonic polyp, acquired by using different endoscopic techniques (a) endoscopy [4], (b) zoom-endoscopy, (c) confocal laser endomicroscopy [5], and (d) WCE (Copyright ©2005-2011, Given Imaging. All Rights Reserved).

tract to be inspected there exist different terms for endoscopic procedures, such as colonoscopy (colon), sigmoidoscopy (inspection of the last part of the colon), gastroscopy or esophagogastroduodenoscopy (upper part of the GI tract down to the duodenum), or endoscopic retrograde cholangiopancreatography (inspection of the bile duct or pancreatic duct).

More recent advances in endoscopy are zoom-endoscopy and chromoendoscopy. Zoom-endoscopy allows to zoom in at regions of interest, using a magnification factor of up to 150. Such devices offer a significant advance since smaller and finer details in the region to be examined get uncovered [6]. Another possibility to obtain images with a higher level of detail are high definition (HD) endoscopes, which also provide images of higher resolutions and therefore allow to detect subtle changes in the mucosa. Chromoendoscopy aims at enhancing superficial patterns on a mucosal layer by topically applying color dyes. An alternative to this rather time-consuming procedure is to use Narrow Band Imaging (NBI), which allows to enhance the contrast of vascular patterns on the mucosal surface [7]. Since NBI is based on a rotating filter in front of the light source (narrowing the spectrum of the visible light to bands of blue and green) this technique is not dependent on applying color dyes. Other systems similar to NBI, like FICE (Fujinon Intelligent Chromoendoscopy) or I-scan, use computer algorithms to post-process endoscopic images. Systems like NBI, FICE, or I-scan are referred to as "virtual chromoendoscopy".

Another recent advance in endoscopy is confocal laser endomicroscopy (CLE) [8]. This procedure allows to inspect the mucosal surface in a highly detailed manner. This is achieved by a laser-based endomicroscope which scans the surface of the mucosa and even allows to inspect sub-surface features up to a depth of 250 microns by adjusting the focal point of the laser. The resulting images have a resolution corresponding to a magnification factor of 1000, making "smart" biopsies possible, thus avoiding random and possibly unnecessary biopsies. Throughout the last years two distinct types of CLE technologies have emerged, namely eCLE and pCLE. While in case of eCLE the endomicroscope is integrated at the distal tip of the endoscope, a CLE probe is inserted into the accessory channel of an endoscope in case of pCLE. Hence, while eCLE and pCLE are similar in terms of the resulting imagery, an endoscope can be easily upgraded with pCLE.

It has already been shown that the diagnostic accuracy of CLE is comparable to histology [9]. It must be noted that CLE actually belongs to the category of flexible endoscopy. Nevertheless, due to the completely different imaging modality in CLE endoscopes, we make a distinction between CLE and flexible endoscopy throughout the remaining part of this work.

Since the small intestine is very long and convoluted a traditional flexible endoscope is only of limited use. A recently developed technique to overcome this limitation and to make endoscopic procedures more safe, less invasive, and more comfortable for the patient, is wireless capsule endoscopy (WCE) [10]. To perform WCE the patient swallows a small capsule, containing a light source, lens, camera, radio transmitter, and batteries. Propelled by peristalsis, the capsule then travels through the digestive system for about eight hours and automatically takes more than 50 000 images. These are transmitted wirelessly to a recorder worn outside the body. Throughout the last years WCE has already proven to be a valuable tool to detect the cause of gastrointestinal bleeding within the small bowel [11]. Recently also other areas of interest for WCE within the GI tract have emerged, such as the colon [12] or the esophagus [13]. But it must be noted that the inspection of these two parts within the GI tract is not well-established yet. Although WCE currently lacks the ability to treat lesions, obtain biopsy samples, and clean poorly prepared areas, this new technique has already proven to be an effective diagnostic modality for detecting small bowel tumors and small bowel lesions [14] since the first approval of a WCE capsule by the FDA (U.S. Food and Drug Administration) in 2001, and may also become an important tool to detect other abnormalities in the GI tract [15].

Another recent advance in endoscopy is virtual endoscopy [16]–[18] (VE), also referred to as computed endoscopy. Since in VE the data to be analyzed is acquired using helical or spiral computer tomography (CT) or Magnetic Resonance imaging (MRI) virtual endoscopy differs significantly from all other techniques described above in terms of the underlying imaging technique. Hence, the remaining part of this work is focused on flexible endoscopy, CLE, and WCE only.

There have been many technological advances throughout the past decades. But while traditional white-light endoscopy is standard-of-care, some techniques mentioned above are still rarely used. While WCE had a deep impact on clinical routine (in particular the investigation of the small bowel), other techniques are still under investigation and thus barely used (i.e. CLE and virtual endoscopy). Other enhancements like NBI or HD endoscopy are not used yet on a regular basis in clinical practice since it is still not clear whether an investment in such systems is worth it.

Sample images for each endoscopic imaging modality mentioned are given in Fig. 2. These images clearly indicate that, while all images show a polyp within the colon, there exist vast differences between the resulting imagery.

## III. Computer-aided decision support systems

A rough overview of common steps involved in a decision support system for medical endoscopy is shown in Fig. 3. In many cases the first step is a preparation of the tissue region to be investigated (e.g. staining, treatment with fluorescent dyes). After an image has been acquired, pre-processing may be required in order to enhance the quality of possibly degraded images. Then, depending on the aim of the application, suitable features have to be found and extracted. Sometimes a post-processing of the features is also necessary (e.g. removing invalid feature combinations in the case of high-level features). If the decision support system is targeted at classification (e.g. polyp detection, cancer detection) the features are used for a classification of the image, using a previously trained classifier. But there also exist other systems which base their decisions directly on the features without using an intermediate classifier (e.g. by using feature thresholds) [19].

Similar to classification, some systems are targeted at content based image retrieval (CBIR) or content based video retrieval (CBVR). The main difference between automated decision support systems and CBIR/CBVR systems is the fact that, in case of an automated decision support, the output of such a system is a suggestion on the final diagnosis or additional information for a diagnosis. This output is usually generated without any intervention by a medical expert needed, potentially allowing, for example, a real-time polyp detection

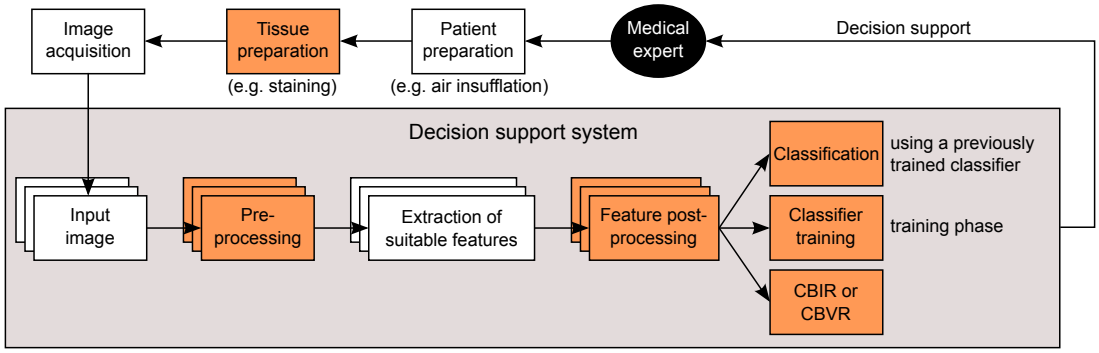



Figure 3. This figure illustrates common steps involved in a decision support system (colored boxes denote optional steps). Layers depict the possibility that multiple frames from an endoscopic video may be processed simultaneously to exploit inter-frame relationships.

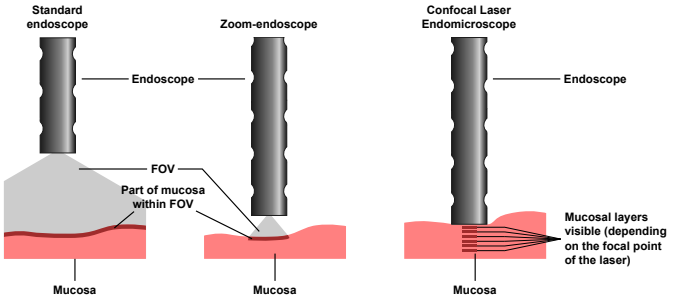



Figure 4. Schematic illustration of the different endoscopic techniques.

while the endoscope is advanced through the colon. CBIR/CBVR systems on the other hand present an expert a number of similar images or videos (on demand), from which the expert is able to decide by himself on the final diagnosis. It is also quite common that the expert is able to interact with the system, allowing a refinement of the search query for similar images. Hence, CBIR/CBVR systems usually have an interactive nature which limits them in terms of real-time capabilities and restricts them to be used for an offline processing.

As already pointed out in Section II, each endoscopic procedure generates images which exhibit specific characteristics depending on the technique used. Therefore, computer systems targeted at decision support must be designed accordingly. As can be seen from Fig. 2(a) an image taken with a traditional flexible endoscope does not allow to see details of the tissue under examination. A zoom-endoscope, on the other hand, allows to examine the fine structures and details of tissue too (see Fig. 2(b)). This, however, comes along with a rather limited field-of-view (FOV), which makes navigation more difficult. This problem is even more apparent in the case of CLE due to the high magnification nature of this technique (see Fig. 2(c)). But this technique produces images which contain clear and detailed structures.

Fig. 4 shows a schematic illustration of standard endoscopy, zoom-endoscopy, and CLE. As can be noticed from this figure the distance of the distal endoscope tip to the mucosa under inspection differs between these techniques. This is due to the different focal depths inherent to the different techniques. As a result, the FOV differs also between the devices. While standard endoscopes usually have FOVs between $120^\circ$ and $170^\circ$, zoom-endoscopes have rather limited FOVs between $50^\circ$ and $70^\circ$. This naturally affects the size of the visible mucosa regions. In case of CLE the FOV is even more limited, resulting in a visible region of about $500 \times 500 \mu m$. Nevertheless, the limited FOV comes along with the advantage of higher image resolutions.

Table I
AN OVERVIEW OF DIFFERENT ENDOSCOPIC IMAGING MODALITIES WITH RESPECT TO THE APPROXIMATE RESOLUTION OF THE PRODUCED IMAGES (GIVEN IN KILOPIXEL) AND THE ABILITY TO PRODUCE COLOR IMAGES.

| Endoscope type | Image resolution | Color images |
|---|---|---|
| Flexible endoscopes | 100 - 500 | Yes |
| Flexible endoscopes (HD) | 900 - 2000 | Yes |
| Capsule endoscopes | 65 - 330 | Yes |
| CLE | 200 - 1000 | No |

In case of WCE the image resolution is often considerably lower compared to the aforementioned techniques (see Fig. 2(d)). In addition, WCE suffers from the inability to control the motion and position of the capsule, which raises new difficulties for CADSSs.

From the example images shown in Fig. 2, it is clear that – even in case of the same pathology – images taken with different endoscopic techniques will in general differ significantly. One particular difference between the different endoscopic modalities is the available image resolution. As shown in Table I, these range from approximately 65 Kilopixel to approximately 2000 Kilopixel. In addition, while some endoscopes allow to capture color images, there also exist endoscopes which capture grayscale images only.

In the next section we present general facts and figures for CADSSs. We discuss the spread of the different endoscopic imaging modalities across CADSS-related literature. This is followed by discussing literature found from the medical perspective of CADSSs. For this purpose we first give an overview of the different parts of the GI tract which CADSSs have been developed for in the past. Then the different pathologies under investigation are outlined, showing the importance of respective detection and classification systems. Finally, we discuss approaches found in literature from the image processing and classification perspective, providing details such as the transformations, features, and classifiers used.

### A. *Facts and figures*

In Section II we already covered the main endoscopic techniques which currently exist to examine the GI tract. From these technologies flexible endoscopy, which includes zoom-endoscopy as well as chromo-endoscopy, is the most commonly used one. Since this technique has been developed about half a century ago, it is no surprise that the first CADSSs, which appeared in the 80's and 90's, were solely focused on this imaging modality.

This however changed with the development of WCE. As can be noticed from Fig. 5 in the year 2004 the first methods focusing on WCE appeared. Since then, a fair amount of WCE-related work has been published. This can be explained by the fact that, as already

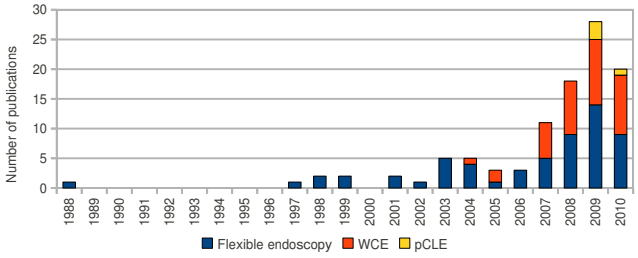



Figure 5. Number of publications on CADSSs throughout the last two decades.

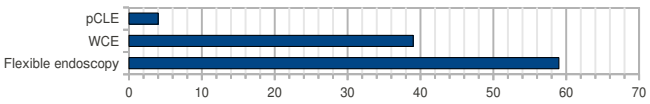



Figure 6. Number of CADSS-related publications found for the different endoscopic image modalities (between 1988 and 2010).

mentioned above, during a WCE session a huge number of images is generated. Since the analysis of all these images by a medical expert is a time consuming task, it is a logical consequence that there is a rising interest in developing CADSSs for WCE.

Because of the fact that CLE is the most recent technique, the number of respective CADSSs targeting this technique is still low. The methods which can be found at the time of this writing are based on pCLE. Up to our knowledge, there exists no CADSSs related work based on eCLE so far.

Fig. 6 shows the number of publications found in literature dealing with CADSSs using the different endoscopic imaging modalities. This figure shows that flexible endoscopy is clearly the most frequently targeted endoscopic technique (about 58%), followed by WCE (about 38%), and pCLE (about 4%).

*1) Areas for CADSSs in the GI tract:* The most important parts of the GI tract, most commonly inspected using an endoscope, can be broken down into the esophagus, the stomach, the small intestine, and the colon. Fig. 7 shows the distribution of the methods found in literature with respect to the different GI tract parts and the endoscopic techniques used. About 71% of the CADSS-related literature focuses on one particular part of the GI tract only. But there also exists a lot of work which aims at examining the complete GI tract and looking out for abnormal pathologies (denoted as "Complete" in Fig. 7). As one can easily see, the majority of these approaches is based on WCE. This is quite natural as the capsule travels through the whole GI tract and therefore a WCE based CADSS is able to search for abnormal pathologies in almost the complete GI tract (basically only restricted by the endurance of the on-board battery).

It is also quite interesting to see that, besides examining the complete GI tract, the colon is obviously the most frequently targeted part of the GI tract (about 50% of the CADSS-related publications).

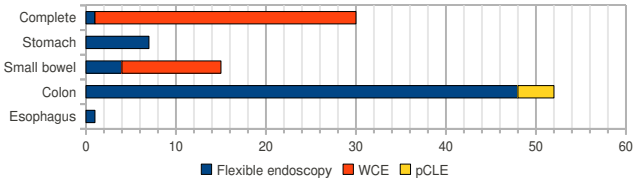



Figure 7. Number of CADSS-related publications per GI tract part (between 1988 and 2010).

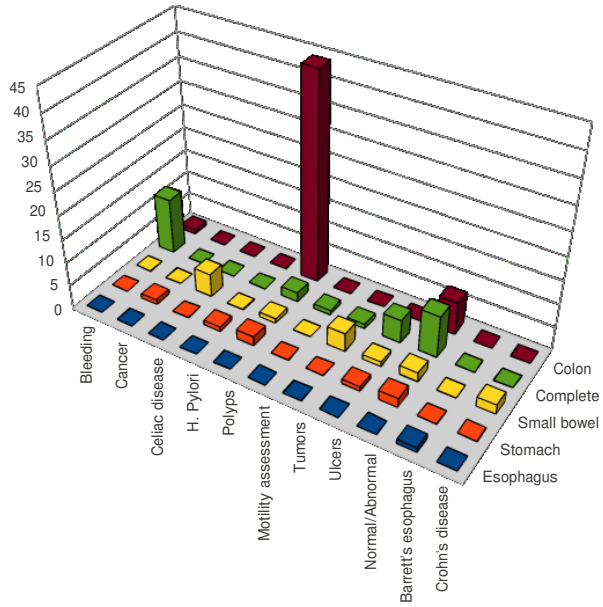



Figure 8. Number of CADSS publications per pathology category and GI tract part (between 1988 and 2010).

This is most probably due to the fact that colon cancer is the third most common malignant disease in western countries. As a consequence, finding abnormalities within the colon is considered a very important field of research. Some of these abnormalities are known to either develop into cancer or to be precursors of colon cancer, hence, an early detection of such pathologies can lower the mortality rate drastically. But also the complete inspection of the GI tract amounts to a rather high share of CADSS-related publications (about 29%). As we have already seen in Fig. 7, the endoscopic imaging modality most frequently used in this case is WCE.

*2) Pathologies under investigation - the medical perspective:* These days endoscopy is used to detect various types of pathologies, as already indicated in Section I. As a consequence there exists a variety of pathologies which are targeted by different CADSSs. Roughly spoken, such systems either try to detect or detect and classify certain pathologies. The respective work from literature is discussed in more detail in Section III-B.

As we notice from Fig. 8, the detection and classification of polyps is the most dominant field of research ($\approx$ 47% of all approaches found in literature), with the colon being the GI tract part of particular interest. This stems from the fact that colonic polyps have a high prevalence, although other parts of the GI tract may also develop polyps. In addition, adenomas are a special type of polyps which, while being benign, carry a high risk of developing into cancer.

Another rather high share of CADSSs-related research focuses on the distinction between normal and abnormal regions ($\approx$ 19%), while not being specific about the underlying pathology.

While gastrointestinal bleeding may be caused by angiodysplasia as well, GI bleeding is quite often an indication for many diseases such as, for example, colon cancer, Crohn's disease, esophageal cancer, small intestine cancer, or the typhoid fever. Hence it is not surprising that the detection of GI bleeding is also the aim of a rather high share of approaches found in literature (about 12%).

The remaining work targets at the detection or classification of other pathologies such as ulcers ($\approx$ 7%), celiac disease, tumors ($\approx$ 5% each), Crohn's disease ($\approx$ 2%), cancer, intestinal dysfunctions, Barrett's esophagus, or Helicobacter pylori ($\approx$ 1% each).

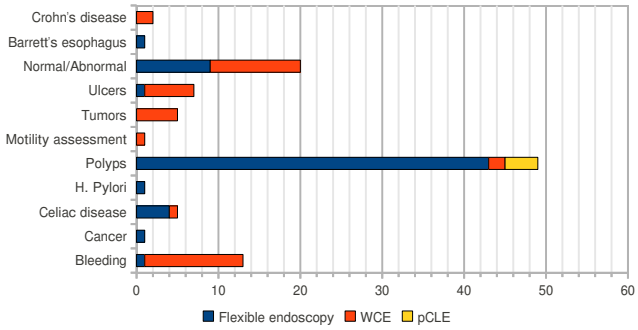



Figure 9. Number of CADSS publications per pathology category (between 1988 and 2010).

From Fig. 9 we notice that the most frequently technique to detect polyps is flexible endoscopy. But also in case of other pathologies this technique is commonly used (e.g. detection of celiac disease or Helicobacter pylori). Nevertheless, we also notice that there exist pathologies where WCE is already the dominant technique. This especially accounts to GI bleeding, ulcers, and Crohn's disease, which may potentially affect various parts of the GI tract.

### *B. Image processing techniques and classification in CADSSs*

In this Section we summarize work on CADSSs found in literature. For this purpose we review the different approaches separated by pathology, grouped by the part of the GI tract the respective methods are targeted at. This is done from the image processing and classification perspective. If a working group has published more approaches which are only slightly different, we discuss the most recent one only.

A more comprehensive overview, including all methods found in literature along with a summary on supportive systems, can be found in a technical report we recently published [3].

*1) Features used:* Throughout the approaches found in literature different types of features are used. These can be roughly categorized into features which are extracted in the spatial domain, those which are extracted in the frequency domain, and those which describe images at a higher level. An overview of these feature categories is given in Table II. In order to cope with various different types of features falling into each category, we also provide a rough subcategorization.

*2) Comparison of approaches:* In order to allow a comparison of approaches, which aim at a computer-aided decision support targeted at endoscopy in the GI tract, we provide a summary of some basic properties of the methods listed in tables III and IV. The following properties have been included in these tables:

- **Reference (denoted by "Ref.")**
  In this column we provide the reference to the respective work.
- **Technique**
  Denotes the endoscopic technique used (i.e. flexible endoscopy, capsule endoscopy denoted by WCE, and probe-based confocal endomicroscopy denoted by pCLE). In case of flexible endoscopy, indicators in columns show whether a certain enhancement has been used ("C" for chromo-endoscopy, "Z" for zoom-endoscopy, "N" for NBI, and "H" for HD endoscopy).
- **Pathology**
  Information about the pathology the respective method aims to detect or classify. If there is no explicit statement made about the underlying pathology, this is denoted by "Abnormalities". In case of Barrett's esophagus, Helicobacter pylori, Crohn's disease, and Motility assessment the abbreviations BE, H. pylori, CrD, CD, and MA are used, respectively.
- **Number of images (denoted by "# imgs")**
  Indicates the number of images available in the image database used. A "N/A" in this column indicates that there is no clear information available on the imagery used.
- **Number of videos (denoted by "# vids")**
  Indicates the number of videos available.
- **Ground truth information**
  The column, denoted by "GT" indicates the methodology used to obtain the ground truth information used throughout the experiments conducted in the respective work ("H" indicates a histologically verified ground truth, while "V" indicates a visually obtained ground truth). "N/A" indicates that the respective publication does not contain any information on the way the ground truth has been obtained.
- **Validation**
  This column indicates the validation protocol which has been used to verify the respective method. LOO-CV, LOPO-CV, LOPIO-CV, and DS are the abbreviations for Leave-one-out cross-validation, Leave-one-patient-out cross-validation, Leave-one-parent-image-out cross-validation, and distinct sets for training and validation, respectively. A "N/A" in this column indicates that there is no clear information on how the verification has been carried out in the experiments.
- **Features**
  Denotes the type of features used in the respective approach. The features, which belong to the different feature types, are listed in Table II (except for feature type "Various", which indicates that the respective method is either based on multiple feature types or that a comparison of different features is carried out). A "N/A" in this column indicates that there is no explicit information available on the features used.
- **Classification**
  This column provides information on how the classification or detection in the respective work has been carried out. SVM, k-NN, ANN, GMM, and DC are the abbreviations for the Support Vector Machines classifier, the k-Nearest Neighbors classifier, different flavors of artificial neural networks or related classifiers, Gaussian Mixture Models, and classifiers based on discriminant analysis, respectively. In case of "Ensemble" the classification is carried out by the combination of different weak classifiers into an ensemble classifier.

From these tables we see that the most commonly used feature types are spatial domain features (used in about 50%) and frequency domain features (used in about 39%), followed by high-level features, which are used in a rather low share of approaches only (about 19%).

We also notice that the most commonly used classifiers are the SVM classifier (used in about 26%), the k-NN classifier (used in about 24%), and some sort of ANN or related network-based classifiers (used in about 21%). The popularity of the SVM classifier can be explained by the fact that it adapts very well to classification problems, even when using high-dimensional features. In addition, usually only a small set of feature vectors is needed for the training of the classifier. The k-NN classifier, on the other hand, is a very simple classifier which nevertheless often achieves competitive classification rates (as compared to other classifiers). ANNs are popular since this type of classifiers, in contrast to SVM and k-NN, is able to adapt to problems by employing different learning schemes.

Another interesting thing we notice from these tables is that the approaches targeted at the detection of GI bleeding are dominated by spatial domain features. This can be attributed to the fact that the most common way to find bleeding is the detection of certain color patterns, which can be achieved fairly well in the spatial domain (e.g. by histograms or thresholding).

Table II
OVERVIEW OF COMMONLY USED FEATURES IN CADSSS TARGETED AT ENDOSCOPY IN THE GI TRACT.

| | |
|---|---|
| **Spatial domain features** | |
| Texture properties | Besides the Local Binary Patterns (LBP) operator, originally proposed in [20], different extensions of LBP have been developed (e.g. uniform (LBPU) and uniform rotation invariant LBP (LBPRIU) [21]). Another extension addresses color-dependencies across color channels (opponent color LBP, OCLBP [22]), The Texture Spectrum transform (TS) is similar to LBP but uses three pixel states for each pixel instead of two [23]. Once a color channel is transformed, usually histograms are computed and used for classification. |
| Pixel-based | In case of these features either pixel intensities are used as features or thresholds are used on pixel data for a final decision on an image. This category also includes different segmentation approaches which are commonly used to detect abnormalities within the GI tract. |
| Histograms | Color histograms or co-occurrence histograms from which usually statistical measures are computed (e.g. Haralick features [24]). |
| Miscellaneous | This category includes MPEG-7 descriptors as proposed in [25], blob analysis, the Bag of visual words method [26] which is based on multiple SIFT descriptors [27] to obtain a scale invariant texture descriptor, and run-length features. |
| **Frequency domain features** | |
| Fourier transform | In different approaches the Fast Fourier transform (FFT) is used to obtain the power spectrum of an image. From this spectrum different statistical features are computed, which are then used for a classification. |
| Wavelets | This type of features is obtained by first applying the Discrete wavelet transform (DWT), the Dual-tree Complex Wavelet transform (DTCWT) [28], the Curvelet transform, or Gabor wavelets. Then, based on the resulting subbands, different features are extracted throughout CADSSs-related literature. These include statistical features computed from the coefficients (e.g. mean, energy, or entropy), Haralick features computed from a co-occurrence matrix computed from the coefficients within a subband, random field parameter estimates on subband coefficients, histograms computed from a LBP-transformed subband, and shape parameters of probability distributions fitted to the wavelet coefficients. |
| **High-level features** | |
| Edge-based | Approaches falling into this category apply some sort of algorithm to detect edges within images (e.g. Canny edge detector or SUSAN edge detector). While some approaches use the edges found directly in order to detect abnormalities (e.g. by using shape matching), usually features based on the edges are extracted (e.g. curvature of edges or other shape descriptors). |
| Region-based | This category of features is based on some sort of segmentation or region growing. Based on the regions found usually features describing these regions or statistical features based on the image content within the regions are computed. Other approaches use the regions found to deduce relationships between the regions (e.g. based on the distance between regions). |

## IV. DISCUSSION

As we have seen in the previous section, there exist various different approaches aiming at assisting a medical expert during the process of decision-making. Apart from that, in Section III we already pointed out that the interest in the field of CADSSs has increased throughout the past two decades. Nevertheless, despite the vast amount of approaches found in literature some common weaknesses exist among a big share of these approaches. In this section we will discuss these issues and propose possible ways to cope with them.

### A. Different image databases

When it comes to the assessment of techniques for CADSSs a common problem are the images or videos used. Although there exist publicly available image databases containing medical images or videos from the GI tract, almost each working group bases their experiments on their own image database, which in most cases has been created in a collaboration with only a few medical experts. As a consequence, work found throughout literature cannot be compared directly. Moreover, it gets nearly impossible for other working groups to verify results presented in this field or to assess the quality of the images used throughout a work (i.e. the medical expertise of the involved experts is usually not known). In Table V we give a short overview of available image databases (abbreviated as DB-1 [4], DB-2 [5], DB-3 [6], DB-4 [7], and DB-5 [8]).

[4]DaveProject, http://daveproject.org
[5]The Gastrointestinal Video Atlas, http://www.gastrointestinalatlas.com
[6]Endoskopie-Atlas, http://www.endoskopiebilder.de
[7]The Atlas of Gastrointestinal Endoscopy, http://www.endoatlas.com
[8]Given Imaging Image Atlas, http://www.capsuleendoscopy.org

Despite the fact that these image databases contain a variety of images and videos, none of these databases can be easily downloaded entirely (the image material has to be downloaded either image by image, video by video, or case by case). Database DB-5 even needs an account to be created in order to be able to download any image material. Another problem, which limits the usability of these databases for an evaluation of automated algorithms, is the fact that none of these databases provides a detailed ground truth for the respective images and videos.

Another issue, which can be frequently observed throughout literature, is the use of a quite limited number of images in some approaches. This is a severe problem, since results based on a few images only must be doubted due to a limited significance. Throughout the work found the number of images used varies significantly as shown in Table VI. This table shows the number of methods which base their experiments on a number of images within a certain range (in absolute values as well as the respective proportions). Since WCE-based work is usually using complete videos, leading to a higher number of images available for experiments, we present these numbers separated by the underlying endoscopic technique (either WCE or flexible endoscopy, including pCLE-based systems). As we notice from this table, most approaches are based on image databases consisting of between 100 and 500 images (41% and 40% in case of WCE and flexible endoscopy, respectively). But there is also work which lacks any information on the quantity of the imagery used or, at least, make no clear statements about the number of images used for training and testing (denoted by "N/A" in Table VI). Such problematic examples can be found in [32], [52], [59], [80], [82], [92], [98]. A special case is constituted by approaches which provide information about the number of videos used but do not give any information about the total number of frames used from these videos

Table III
OVERVIEW OF CADSS-RELATED APPROACHES TARGETING AT THE GI TRACT FOUND IN LITERATURE.

| Ref. | Technique | Pathology | # imgs | # vids | GT | Validation | Features | Classification |
|---|---|---|---|---|---|---|---|---|
| **Esophagus** | | | | | | | | |
| [29] | Flexible | BE | 390 | - | H | LOO-CV | Spatial | k-NN |
| **Stomach** | | | | | | | | |
| [30] | Flexible | H. pylori | 236 | - | H | k-fold CV | Frequency | SVM |
| [31] | Flexible | Polyps | 1000 | - | N/A | k-fold CV | Various | SVM |
| [32] | Flexible | Ulcers | N/A | - | N/A | N/A | High-level | - |
| [33] | Flexible | Cancer | 176 | - | V | k-fold CV | Spatial | k-NN, SVM, Bayes |
| [34] | Flexible | Abnormalities | 2949 | - | V | DS | Spatial | Ensemble |
| [35] | Flexible | Abnormalities | 534 | - | V | k-fold CV | Spatial | Ensemble |
| **Small bowel** | | | | | | | | |
| [36] | WCE | Tumors | 396 | - | V | DS | Frequency | ANN |
| [37] | WCE | Tumors | 600 | - | V | DS | Frequency | ANN |
| [38] | WCE | Tumors | 600 | - | V | DS | Frequency | ANN, GMM |
| [39] | WCE | Tumors | 300 | - | V | k-fold CV | Frequency | SVM |
| [40] | WCE | Polyps | 128 | - | V | DS | High-level | Thresholding |
| [41] | WCE | Ulcers | 80 | - | V | k-fold CV | Spatial | SVM, DC |
| [42] | Flexible | Celiac disease | 192 | - | H | LOO-CV | Frequency | k-NN, SVM, Bayes |
| [43] | Flexible | Celiac disease | 84 | - | H | LOO-CV | Frequency | k-NN, SVM, Bayes, Ensemble |
| [44] | Flexible | Celiac disease | 273 | - | H | LOO-CV | Various | k-NN |
| [45] | WCE | Celiac disease | 21000 | 105 | V | N/A | Spatial | DC |
| [46] | WCE | CD | 13689 | - | V | DS | Spatial | SVM |
| [47] | WCE | CD | 746 | - | V | DS | Spatial | SVM |
| [48] | WCE | Abnormalities | 75 | - | V | LOO-CV | Frequency | Thresholding |
| **Colon** | | | | | | | | |
| [49] | Flexible | Polyps | 15000 | 60 | H | DS | Various | SVM |
| [50] | pCLE | Polyps | 1036 | - | H | k-fold CV | Spatial | k-NN |
| [51] | pCLE | Polyps | 4449 | 499 | H | LOPO-CV | Spatial | k-NN |
| [52] | Flexible | Polyps | N/A | - | N/A | N/A | Spatial | Fuzzy rules |
| [53] | Flexible (Z) | Polyps | 7 | - | V | N/A | Spatial | - |
| [54] | Flexible | Polyps | 35 | - | V | k-fold CV | Spatial | SVM |
| [55] | Flexible (H) | Polyps | 1736 | - | V | k-fold CV | Spatial | SVM |
| [56] | Flexible | Polyps | 74 | - | V | DS | Spatial | SVM |
| [57] | Flexible | Polyps | 8 | - | N/A | DS | Frequency | ANN |
| [58] | Flexible | Polyps | 2 | - | H | DS | Various | ANN |
| [59] | Flexible | Polyps | 8 | - | N/A | DS | Frequency | ANN |
| [60] | Flexible | Polyps | 1380 | - | H | DS | Frequency | DC |
| [61] | Flexible | Polyps | - | 60 | V | DS | Frequency | SVM |
| [62] | Flexible | Polyps | 4 | - | N/A | DS | Spatial | ANN |
| [63] | Flexible (C/Z) | Polyps | 257 | - | H | LOO-CV | Spatial | k-NN |
| [64] | Flexible (C/Z) | Polyps | 484 | - | H | LOO-CV | Frequency | k-NN |
| [65] | Flexible (C/Z) | Polyps | 484 | - | H | LOO-CV | Frequency | k-NN |
| [66] | Flexible (C/Z) | Polyps | 484 | - | H | LOO-CV | Frequency | k-NN |
| [67] | Flexible (C/Z) | Polyps | 484 | - | H | LOO-CV | Various | Ensemble |
| [68] | Flexible (C/Z) | Polyps | 484 | - | H | LOO-CV | Frequency | k-NN, Bayes |
| [69] | Flexible (C/Z) | Polyps | 627 | - | H | LOO-CV | Spatial | k-NN |
| [70] | Flexible (C/Z) | Polyps | 484 | - | H | LOO-CV | Frequency | Ensemble |
| [71] | Flexible (C/Z) | Polyps | 627 | - | H | LOO-CV | Frequency | k-NN |
| [72] | Flexible (C/Z) | Polyps | 484 | - | H | LOO-CV | Frequency | Bayes, SVM, DC |
| [73] | Flexible (C/Z) | Polyps | 627 | - | H | LOO-CV | High-level | k-NN |
| [74] | Flexible (C/Z) | Polyps | 627 | - | H | LOO-CV | High-level | k-NN |
| [75] | Flexible (C/Z) | Polyps | 627 | - | H | LOPIO | Frequency | k-NN |
| [76] | Flexible (N) | Polyps | 102 | - | H | N/A | High-level | k-NN |
| [77] | Flexible (N) | Polyps | 56 | - | H | N/A | High-level | k-NN |
| [78] | Flexible (N/Z) | Polyps | 209 | - | H | LOO-CV | High-level | SVM |
| [79] | Flexible | Abnormalities | 9 | - | N/A | N/A | High-level | Fuzzy rules |
| [80] | Flexible | Abnormalities | N/A | - | N/A | N/A | High-level | Thresholding |
| [81] | Flexible | Abnormalities | 22 | - | N/A | DS | High-level | ANN |
| [82] | Flexible | Abnormalities | N/A | - | N/A | N/A | Spatial | - |
| [83] | Flexible | Abnormalities | 66 | - | N/A | DS | Spatial | ANN |
| [84] | Flexible | Abnormalities | 2 | - | N/A | DS | Spatial | ANN |
| [85] | Flexible | Abnormalities | 58 | - | V | LOO-CV | Frequency | Ensemble |

[61] (denoted by "Videos" in Table VI).

Image databases consisting of less than 100 images are not suitable to estimate the accuracy of a CADSS. Using between 100 and 500 images may already be sufficient to support presented results. While using more than 500 images seems to be more appropriate in order to achieve reliable and significant results (used in about 33% and 24% of all work in case of WCE and flexible endoscopy, respectively), we have to point out that the sufficiency also depends on the number of image classes used in a work.

While in other fields of research (e.g. biometrics) the use of well-established databases is already common practice, this is still not the case in the field of CADSSs. Nevertheless, it is absolutely necessary to establish commonly used image databases (depending on the underlying endoscopic technique), containing a sufficient amount of images and made available to researchers in this field. Especially in cases where a visual inspection is common practice to obtain the

Table IV
OVERVIEW OF CADSS-RELATED APPROACHES TARGETING AT THE GI TRACT FOUND IN LITERATURE.

| Ref. | Technique | Pathology | # imgs | # vids | GT | Validation | Features | Classification |
|---|---|---|---|---|---|---|---|---|
| **Complete GI tract** | | | | | | | | |
| [86] | WCE | Bleeding | 100 | - | V | N/A | Spatial | Thresholding |
| [87] | WCE | Bleeding | 14630 | - | V | N/A | Spatial | ANN |
| [88] | WCE | Bleeding | - | 5 | V | DS | Spatial | Ensemble |
| [89] | WCE | Bleeding | 2000 | - | V | N/A | Spatial | Thresholding |
| [90] | WCE | Bleeding | 1111 | 11 | V | N/A | Spatial | - |
| [91] | WCE | Bleeding | 1705 | 5 | V | N/A | Spatial | Thresholding |
| [92] | WCE | Bleeding | N/A | - | V | N/A | Spatial | - |
| [93] | WCE | Bleeding | 200 | 10 | V | DS | Various | ANN |
| [94] | WCE | Bleeding | 6416 | - | V | DS | Spatial | SVM |
| [95] | WCE | Bleeding | N/A | - | V | N/A | Spatial | ANN |
| [96] | WCE | Tumors | 1200 | - | V | k-fold CV | Frequency | SVM |
| [97] | WCE | MA | - | 172 | V | LOO-CV | High-level | SVM |
| [98] | Flexible | Polyps | N/A | - | V | N/A | High-level | Thresholding |
| [99] | WCE | Polyps | 50 | - | V | N/A | High-level | Thresholding |
| [100] | WCE | Ulcers | 60 | - | V | DS | High-level | SVM |
| [101] | WCE | Ulcers | 200 | 10 | V | DS | Frequency | SVM, ANN |
| [102] | WCE | Ulcers | 250 | - | V | DS | N/A | ANN |
| [103] | WCE | Abnormalities | 140 | - | V | DS | Spatial | Fuzzy logic |
| [104] | WCE | Abnormalities | 140 | - | V | DS | Spatial | Fuzzy logic |
| [105] | WCE | Abnormalities | 60 | - | V | LOO-CV | Spatial | Centroid |
| [106] | WCE | Abnormalities | 87258 | - | V | DS | Frequency | ANN |

Table V
OVERVIEW OF PUBLICLY AVAILABLE IMAGE DATABASES DEALING WITH ENDOSCOPY IN THE GI TRACT. THE COLUMNS V AND I INDICATE THE NUMBER OF VIDEOS AND IMAGES AVAILABLE, RESPECTIVELY. IN THE COLUMN "REGIONS" E, ST, SB, AND C ARE ABBREVIATIONS FOR ESOPHAGUS, STOMACH, SMALL BOWEL, AND COLON, RESPECTIVELY (INFORMATION COLLECTED ON THE 25TH OF NOVEMBER, 2010).

| Name | Modality | V | I | Regions | Case details | Registration required |
|---|---|---|---|---|---|---|
| DB-1 | Various | 804 | N/A | E, ST, SB, C | Yes | No |
| DB-2 | Various | 3521 | N/A | E, ST, SB, C | Yes | No |
| DB-3 | Various | <75 | >1000 | E, ST, SB, C | No | No |
| DB-4 | Various | N/A | 1076 | E, ST, SB, C | Yes | No |
| DB-5 | WCE | 85 | 85 | E, SB, C | No | Yes |

Table VI
NUMBER OF APPROACHES WHICH ARE BASED ON THE GIVEN NUMBER OF IMAGES ALONG WITH THE RESPECTIVE PROPORTIONS.

| # of images | WCE | | Flexible endoscopy | |
|---|---|---|---|---|
| < 100 | 7 | 18 % | 17 | 27 % |
| 100 – 500 | 16 | 41 % | 25 | 40 % |
| > 500 | 13 | 33 % | 15 | 24 % |
| Videos | 1 | 3 % | 1 | 1 % |
| N/A | 2 | 5 % | 5 | 8 % |
| | 39 | 100 % | 63 | 100 % |

ground truth information, involving several different medical experts in the process of creating such a database would be necessary to lower the inter-observer disagreement.

As a consequence of the usually limited image databases many methods are not evaluated on two distinct image sets (one for the training and one for the validation of the underlying classifier). Different sets are only used in about 31% of all methods found in literature. The remaining work is either based on some variant of cross-validation [107] (in about 50%) or the authors provide no clear information about the training- and validation-strategy used (in about 20%). While cross-validation is a common way to deal with small image databases there also exist pitfalls. One problem is a possible overfitting if two or more images in the database originate from the same patient and have been taken in the very same region within the GI tract. Depending on the features used, the feature vectors for such images are likely to exhibit a high similarity. To cope with this problem the Leave-One-Patient-Out (LOPO) cross-validation is an option, ensuring that the training set does not contain images from patients in the validation set. However, this type of cross-validation is rarely used throughout literature (in only about 4% of the methods using cross-validation). Another pitfall arises when some sort of feature selection is used along with cross-validation. In this case it is important to perform the cross-validation on each feature candidate set in order to avoid overfitting (inner cross-validation) [108].

In order to facilitate a meaningful evaluation of methods aiming at computer-aided decision support, researchers working on this topic should at least adhere to the following key advices:

- The image database behind published results should be made available to the public whenever possible.
- Published results should be accompanied by as many details about the images used as possible (e.g. image dimensions, color or grayscale, number of images used or the number of patients in the database).
- Image databases used for the evaluation of approaches should contain a sufficient number of images (500 images or more).
- If the image database used is sufficiently large it is advisable to split the image set into separate sets for training and validation.
- For small image databases Leave-One-Patient-Out cross-validation must be preferred over Leave-One-Out cross-validation (if splitting into separate sets for training and validation is not possible).

### *B. Ground truth establishment*

Basically there exist two different ways of obtaining ground truth information for experiments. The respective class labels may be gathered either by a visual inspection of endoscopic imagery or based on histological findings.

If the ground truth is obtained by visual means there is no profound knowledge about the real pathology for a given image. In addition,

the judgment on the pathology in case of a visual inspection may differ significantly between different experts (i.e. the inter-observer agreement may be rather low, depending on the level of expertise of the experts).

For WCE-based CADSS there is usually no other option than to rely on visual inspections by one or more medical experts, since taking biopsies is not possible with current capsule endoscopes.

In case of flexible endoscopy the ground truth can be gathered histologically since taking biopsies is possible. But even if histological findings are available, an endoscopic image does not necessarily correspond to the biopsy site due to slight movements of the endoscope tip, which for example may be the result of the preparation for taking a biopsy (especially in case of magnified endoscopy).

A special case is constituted by CLE since this technique allows in-vivo histologies due to the high level of magnification. As already stated earlier, it has already been shown that the diagnostic accuracy of CLE is comparable to histology [9], [109], [110]. Hence, the inter-observer agreement is also expected to be similar to the agreement in case of histology.

Considering the existing methods which are based on flexible endoscopy (including pCLE), 10 out of 63 methods base their experiments on a visually obtained ground truth (about 17%), while the vast majority of the methods (40 out of 63) is based on histological findings (about 65%). However, there are also quite a few approaches which do not unveil the way the ground truth has been obtained (12 out of 63 approaches, which corresponds to about 19%) [31], [32], [52], [57], [59], [62], [79]–[84].

Making a recommendation concerning this issue is not easy, since the best way of obtaining the ground truth information very much depends on the endoscopic technique used. While in case of WCE a visual inspection is usually the only way a ground truth can be obtained, in case of pCLE a visual ground truth gathering is likely to be sufficient due to its closeness to histology. In case of the remaining work based on flexible endoscopy a histological ground truth is highly desired due to its accuracy over visual inspection.

If one has to rely on a visually obtained ground truth, because a histological ground truth is not available, it is imperative to make the respective ground truth as reliable as possible. Usually this is achieved by consulting different medical experts for a visual inspection of the imagery. This allows to take care of a probably low inter-observer agreement due to different levels of expertise among different experts, by using images only which have been classified by various experts into the same image class with high confidence. A similar way of making a visually obtained ground truth more reliable has been chosen for example in [33]. In a second classification stage Sousa et al. resolve inter-observer discrepancies by analyzing and re-classifying images which have been classified differently with high confidence by the medical experts in the first classification round.

However, no matter how the ground truth has been obtained, each method published in this field of research should be accompanied by this information to make it possible for a reader to make his own judgments on the value of the results presented.

### C. Accuracy and computational complexity

Since existing approaches do not only focus on different parts within the GI tract but also target different pathologies, a direct comparison in terms of the respective classification performance is not possible. Despite the fact that there exist different ways to measure the accuracy of a system, we also identified work in the literature which does not provide any results at all (8 out of 102 approaches, which corresponds to about 8%) [32], [52], [53], [79], [80], [82], [92], [98]. This makes a comparison against other methods impossible. However, even if some sort of accuracy information is given this does not automatically imply that the proposed systems are comparable. This stems from the fact that a number of different measures to rate a system have been established throughout literature. These measures include the overall classification accuracy (i.e. the total number of correctly classified images divided by the total number of images), the sensitivity (also known as recall), the specificity, and area under ROC curves.

While the overall accuracy allows us to get an idea of how well a method performs there is no evidence about the false positives or false negatives produced by the system, which however is of particular interest for medical experts. ROC plots also give an idea of the overall system performance by the investigation of the area under the curve.

To make comparison among different systems feasible it is therefore necessary to establish a set of measures which are then used to assess the classification performance throughout diagnosis systems (e.g. overall classification rate, specificity, and sensitivity). But even if the same measures are used a direct comparison of different approaches is not meaningful if the experiments are based on different image databases. But at least a rough comparison would be possible. Using limited or unbalanced datasets is also problematic as in such cases the results are usually of low significance or biased.

In Table VII we give an overview of the overall accuracies, specificity values, and sensitivity values, respectively, which have been reported in work targeted at diagnosis (no distinction is made between detection and classification). This table contains the respective ranges of the reported values. In addition, the references of the approaches which achieved the highest values are given. As we notice from this table there are some pathologies which are already detected (or classified) with a rather high accuracy (above 95%). These include GI bleeding, celiac disease, polyps, and the distinction between normal and abnormal cases. Also in case of the sensitivities and specificities reported we already see rather high values (always above 90%). But since the results are based on different image databases, which limits the comparability between approaches, the main purpose of this table is to give a rough overview of the results reported throughout literature.

Another issue concerning the comparison of methods within a publication is the statistical significance. Even if two methods deliver different classification accuracies this does not automatically imply that the difference is statistically significant. To assess the statistical significance tools to compute a p-value have been established (for example the McNemar test [113]). Especially in medical literature giving evidence for statistical significance is common practice. Throughout the literature investigated within this work, however, such information is only given in a very few cases. Due to the reasons mentioned above measuring the statistical significance across different methods is hardly possible.

Another issue, which however is of minor importance, is the computational complexity of systems proposed in literature. For WCE based systems complexity issues are of minor interest since these systems are usually designed to process images or videos offline (i.e. not in real-time). However, for other systems, which possibly allow real-time processing of images and videos, information about the computational demand may be of interest since other researches may base their decision on using a proposed method or not on this information. But it must be noted, that while complexity information is given in a very few cases only, one is usually able to at least roughly estimate the computational demand of a system if the work is based on well-known algorithms (e.g. frequency transforms, edge detection methods, statistical texture features). But including at least rough estimates of the computational demand of a proposed

Table VII
THE RANGES OF OVERALL ACCURACIES, SENSITIVITIES, AND SPECIFICITIES REPORTED AMONG THE WORK FOUND IN LITERATURE (GIVEN IN PERCENT). A REFERENCE TO THE WORK REPORTING THE RESPECTIVE MAXIMUM VALUE IS GIVEN TOO.

| Target of work | Accuracy | Reference | Specificity | Reference | Sensitivity | Reference |
|---|---|---|---|---|---|---|
| Barrett's esophagus | 81 | [29] | - | | - | |
| Bleeding | 87 - 99 | [95] | 86 - 93 | [93] | 83 - 93 | [87], [89] |
| Cancer | 91 | [33] | - | | - | |
| Celiac disease | 72 - 98 | [42], [111] | 84 - 100 | [42] | 53 - 100 | [111] |
| Crohn's disease | 87 - 96 | [46] | 93 | [47] | 70 - 80 | [47] |
| H. pylori | 87 | [30] | - | | - | |
| Motility assessment | - | | 100 | [97] | 95 | [97] |
| Normal/Abnormal | 85 - 100 | [81] | 76 - 98 | [103] | 65 - 97 | [48], [103] |
| Polyps | 74 - 99 | [64], [69] [57], [71] | 67 - 99 | [63], [66] [60], [112] | 56 - 100 | [67], [99] [40] |
| Tumors | 88 - 97 | [39] | 96 - 97 | [37] | 97 - 99 | [36], [38] |
| Ulcers | 74 - 95 | [41] | 73 - 95 | [41] | 75 - 95 | [41] |

method (separately for e.g. pre-processing, training, classification or detection) may be helpful.

Nevertheless, the approaches available so far deliver results which are not good enough to be used in clinical practice. As a consequence the computational complexity of algorithms is, at least currently, of minor importance.

## V. CONCLUSION AND FUTURE RESEARCH

In this work we gave an overview of research mainly focused at the detection or classification of different pathologies of interest in endoscopy of the GI tract. We noticed that there is a rising interest in this research topic, especially throughout the last two decades. We also gave an overview of different parts within the GI tract and respective pathologies of current research interest.

Considering the importance of CADSSs and the benefits of such systems (like saving time and therefore lowering the cost for endoscopic procedures or improving the quality of diagnosis) the interest in CADSSs targeted at the GI tract is expected to increase even more in the future. Especially when considering the fact that for many diseases an early detection may decrease the mortality rate significantly, the need for reliable CADSSs gets even more apparent.

Since capsule endoscopy already had a great impact on clinical routine as it has already proven to be an effective diagnostic modality, an increasing interest has already been seen for this endoscopic image modality. This especially accounts to GI bleeding detection where finding the cause is hardly feasible when using other endoscopic imaging modalities. While not discussed in this review, also the pre-selection of important frames out of a complete WCE video is of special interest when considering the high number of images generated during a WCE exam. This allows a medical expert to interpret the outcome of an exam more quickly.

But one can also expect a rising interest within the next years when it comes to other, more recent technological advances like CLE. However, with the advent of new technologies the key challenges in developing CADSSs for endoscopy are also likely to change slightly. Currently the major challenges include the detection and handling of image degradations (e.g. reflections and sensor noise), finding robust features to detect and classify different pathologies properly, and finding regions of interest in an automated fashion. In CLE-based systems, for example, this slightly changes. While degradations are a minor problem with this technique, other limitations like for example the limited FOV and the rather high zoom factor pose new problems. As a consequence, currently one major research area in case of CLE is so-called mosaicking, which enlarges the mucosal area visible to a medical expert by employing stitching algorithms. Besides that, the endoscopist is facing new challenges (examination at a microscopic level which requires a histopathological training). This indicates that systems for an automated classification of lesions are an important field for future research when working with CLE endoscopes.

While new imaging modalities have the potential to greatly increase the efficiency of endoscopy, medical experts need to get trained on these new techniques. In order to steepen the learning curve for medical experts on certain new endoscopic techniques CADSSs may also be used as an expert training tool to predict pathology, verify the detection or prediction performance of a medical expert, and serve as an educational resource.

From the approaches reviewed in this work we notice that the majority of approaches is based on still images. However, an endoscopy session usually generates videos. Hence, we consider the analysis of videos to be a prospective field for future research. This would allow to incorporate temporal information into classification and detection systems as well. In addition, this might help to limit the effect of image degradations since those can be separated more easily from the important content by an analysis based on more than one image.

Despite the fact that there is a lot of research going on in the area of CADSSs for endoscopy in the GI tract, there are also some strong weaknesses existing among the literature reviewed which hamper such systems from being used in clinical practice.

Besides the still rather low classification accuracies of such systems, one of the biggest issues is the fact that there is a high diversity of image databases used throughout literature. Some of these image databases are even way too small, resulting in a rather low expressive power concerning the results presented within the respective publications. Part of this problem is also that at the moment there exists no publicly available database which could be used among researchers to compare their results in a meaningful manner. Hence, in order to allow the development and evaluation of systems to be used in clinical practice this major problem must be tackled by creating reasonable image databases (i.e. sufficiently large, publicly available, and provided with a meaningful and reliable ground truth information).

Considering the system accuracies already achieved for the different pathologies of interest and the number of publications found, we currently consider bleeding detection, polyp and tumor detection and classification to be the most mature fields. We therefore believe that the first clinically used systems will be available within these areas of research – although this may take some more years.

Reaching a higher level of reliability in upcoming CADSSs will also strongly depend on advances in the hardware used to acquire the underlying image material. There are still some limitations imposed by the hardware available, which leave room for improvement as well (e.g. poor image quality). But as we have shown in this work, endoscopic devices are improved more and more (in terms of patient comfort, image quality, or just to overcome current limitations).

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