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Vision-based personalized Wireless Capsule Endoscopy for smart healthcare: Taxonomy, literature review, opportunities and challenges

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ABSTRACT

Wireless Capsule Endoscopy (WCE) is a patient-friendly approach for digestive tract monitoring to support medical experts towards identifying any anomaly inside human's Gastrointestinal (GI) tract. The automatic recognition of such type of abnormalities is essential for early diagnosis and time saving. To this end, several computer aided diagnosis (CAD) methods have been proposed in the literature for automatic abnormal region segmentation, summarization, classification, and personalization in WCE videos. In this work, we provide a detailed review of computer vision-based methods for WCE videos analysis. Firstly, all the major domains of WCE video analytics with their generic flow are identified. Secondly, we comprehensively review WCE video analysis methods and surveys with their pros and cons presented to date. In addition, this paper reviews several representative public datasets used for the performance assessment of WCE techniques and methods. Finally, the most important aspect of this survey is the identification of several research trends and open issues in different domains of WCE, with an emphasis placed on future research directions towards smarter healthcare and personalization.

1. Introduction

WCE is a relatively new technology when compared to conventional endoscopy methods for visualization of the digestive tract. It was introduced in 2000 and approved in 2001 by Food and Drug Administration for clinical practice due to its portability and ease of usage for healthcare services [1]. In a WCE procedure, a pill-sized capsule with camera attached at its head is swallowed by the patient. The camera captures the video stream and transmits it to a portable device called "image recording unit", which is attached to the patient's body along with an antenna array of several leads [2]. The expelling time of capsule from human body in a natural way, is approximately 72 h, of which the video stream corresponding to the initial eight hours is important for visualizing the GI tract [3]. An average of 50,000 frames are captured in the eight hours' duration depending on the capturing rate of the underlying capsule. It is widely accepted in this area that all the collected frames are not diagnostically important because there is significant redundancy and non-informative frames. The reason for this redundancy is the explosion of capsule to turbid fluids and other food particles of GI tract when passing through the tract [4]. Traditionally, the patient needs to visit the hospital, where the endoscopy set is dispatched, and video data is copied to the system for diagnostic process. For a complete guide about WCE, readers are referred to [5].

Considering the huge amount of video data and its inherent redundancy, it is unfeasible for gastroenterologists to localize their desired diagnostically important frames due to the excessive time needed for manual inspection. According to [6], a clinician needs on average two hours to view around 50,000 images and issue a diagnostic recommendation for a single patient. In addition, the sharing of this large amount of data with doctors for patients in remote areas is challenging for 'in-time' observation and diagnosis. In this context, it is necessary to have a degree of automation for such huge-sized data, which can discriminate the important frames from the non-important ones. Video summarization/prioritization is a mechanism that can solve this problem by eliminating and discarding the redundant and non-informative frames, respectively [7,8]. Besides prioritization, automatic methods are needed for segmentation [9] and anomaly detection [10–12] in the WCE frames for better analysis. To this end, researchers have conducted several studies for segmentation, detection, and

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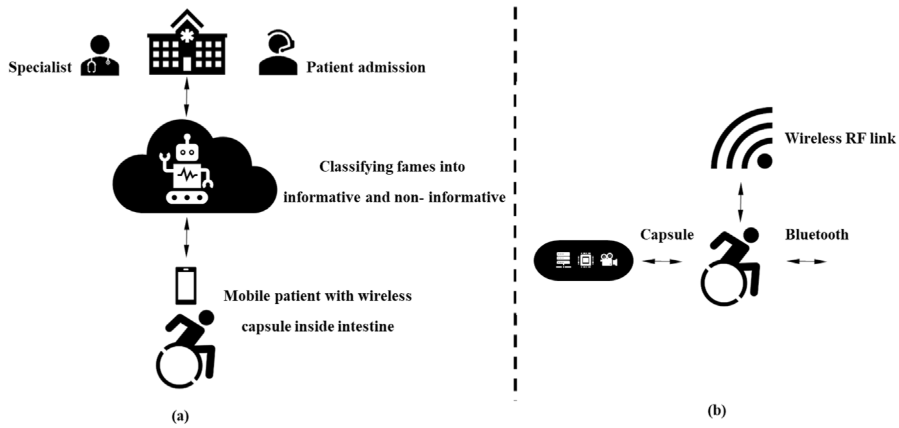

Fig. 1. Video summarization-assisted WCE procedure for personalized and smart healthcare [4]; (a) Redundant frames are discarded on-the-fly using patient's smartphone because a lightweight redundancy removal method is employed for this step. The classification process is offloaded to cloud due to its excessive power usage and critical nature because the frames classified as "diagnostically important" will be directly observed by gastroenterologists for diagnosis. (b) An overview of working scenario of WCE with smartphone for smart healthcare.

classification of WCE data using the publicly available datasets given on GASTROLAB site [13] and used in [14–20].

The recent progress in sensor technologies has resulted in new smart devices for medical field, especially for e-health from which patients in remote areas with limited access facilities to hospitals can greatly benefit [21,22]. For instance, gait analysis is a medical diagnostic process with numerous applications in healthcare, but needs to be performed in a laboratory, which is not accessible for majority of the population in developing countries. Many contributions in the literature have addressed this particular issue. For instance, Feng Lin et al. [23] developed "Smart Insole", a wearable sensor device that is lightweight and comfortable and can unobtrusively perform gait monitoring for remote patients. Consequently, gait analysis can be used in diagnostic process of numerous diseases i.e., Parkinson's disease, Huntington, and stroke [24,25]. Similarly, Sundaravadivel et al. [26] presented "smart-long", an automated nutrition monitoring system supported by IoT platform. Their system can be mainly used for either infants at home or at daycare facilities, thus taking a step further on current healthcare systems for nutrition monitoring. Besides smart sensors, the improved processing capabilities of smartphones have enabled them to perform different healthcare operations, which can contribute to the cost-effectiveness of remote healthcare systems. For instance, the patient's smartphone can be used to perform lightweight processing for the data generated during an ongoing diagnostic process, such as the identification and discarding of redundant video frames during WCE. A representative system in this context is presented in [4], with its main framework illustrated in Fig. 1(a). The process is personalized by using the patient's smartphone and adjusting different parameters related to its operation, such as the required energy for processing, transmission cost, or smartphone's battery life among others alike (see Fig. 1(b)).

To motivate researchers towards intelligent WCE video analytics, this prospective survey reviews the existing literature and divides methods reported so far into four different domains: segmentation/detection, redundancy removal/summarization, classification/recognition, and personalization. All the existing methods are targeting one or multiple of these domains using different AI-enabled techniques. In this manuscript, we provide a brief overview of all WCE video analysis methods, towards identify their major achievements and limitations. In addition, we also present a comparative analysis of our survey with existing reviews in the literature gravitating on WCE video analytics. Furthermore, we shortlist the publicly available datasets used for the evaluation of WCE. Finally, we identify current challenges that remain insufficiently addressed in this research area, and provide future directions and recommendations for interested researchers to overcome these challenges. The main contributions of this survey can be summarized as follows:

1. A detailed critical review of existing WCE methods is provided along with their targeted domains, key accomplishments, and major limitations. Unlike other existing works, we perform a comparative analysis of this survey with existing ones, benchmark datasets and their usage, and most importantly, current research trends and recommendations for the future of the area.
2. We establish a taxonomy that organizes WCE video analytics as per four different domains: segmentation/detection, redundancy removal/summarization, classification/recognition, and personalization. The main aim of this division is to show the basic workflow of each domain, and develop the interest of researchers towards these research areas. In addition, it also stimulates the development of hybrid-personalized methods that include all these facilities to deal with remote patients for smart healthcare services.
3. Current challenges of all domains of WCE images/videos analytics are provided and discussed in depth, stepping on the main drawbacks and research niches observed in our review of existing literature. Based on our conclusions and prospects, we also advocate for several practical guidelines and recommendations for the research community to steer their contributions in proper and fruitful directions along all domains of WCE analytics.

The remaining study consists of five sections. Section 2 provides the comparative analysis of our study with existing WCE surveys. Section 3 presents an in-depth review of WCE methods and their division into four different domains. The publicly available datasets and current challenges with future recommendations are discussed in Section 4 and Section 5, respectively. Finally, Section 6 concludes this survey with its key findings.

2. Existing WCE surveys

This section provides a detailed comparative analysis of existing WCE images and videos analytics surveys published in the past eleven years. The summarized information of these surveys is given in Table 1, with six key metrics including published year,

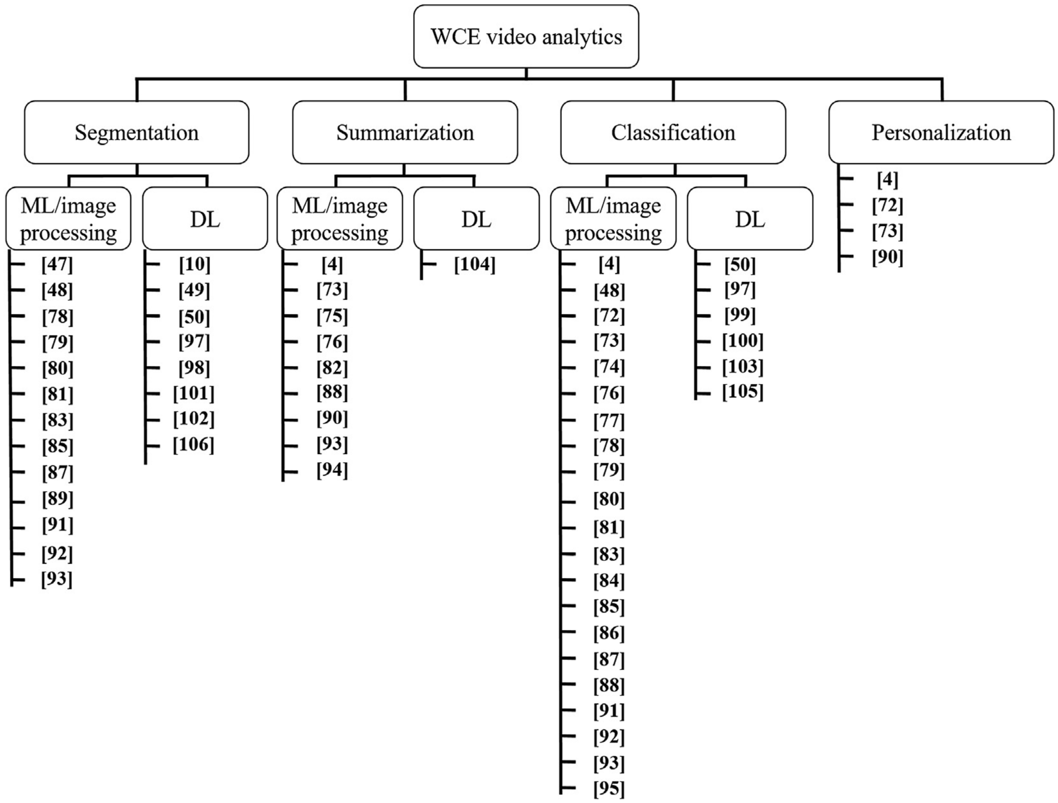

Fig. 2. A Taxonomy of WCE images and video analytics methods into four major domains and a further sub split into two Machine Learning (ML)/image processing based methods and Deep Learning (DL) based methods. On top of them, the Taxonomy also illustrates that some methods targeted multiple domains of WCE images/video analytics.

literature coverage, total number of papers reviewed, consideration of existing surveys, datasets coverage, and finally the scope of each literature study.

Besides these evaluation metrics, there are several limitations of these methods, which stimulates the need for a more a compact reference material for future contributions made in this area. For instance, the major limitations of [27,28], and [29] are the lack of a targeted application area, and the absence of an analysis of the trends detected in the surveyed topic. Furthermore, the surveys conducted in 2015 and 2017 have a narrow research coverage i.e., they are restricted to only one type of tumor/anomaly detection or segmentation in WCE. In addition, the key limitations of more recent surveys presented in 2018 and 2019 neglect the importance of personalization and smart healthcare and deficiency of current challenges and future directions, which are the most important aspects of every survey, acting as a tool to encourage the research community for further development. Keeping these limitations in mind, we propose the current survey for personalized WCE, with a view on its usage in the context of smart healthcare. As mentioned in the introduction, our survey facilitates a detailed comparative analysis of existing surveys, sorts and comprehensively reviews WCE methods published so far in four major domains, comments on publicly available datasets, and explores current challenges with an outlook towards research lines that deserve further attention from the related community.

3. Reviewed WCE methods

The methods presented in the current literature for WCE data analysis can be classified into a taxonomy comprising four different domains: segmentation/detection, redundancy removal/summarization, classification/recognition, and personalization. These domains are further divided into machine learning and deep leaning based methods as illustrated in Fig. 2. The complete detail about each of these domains are given in subsequent sections.

3.1. Segmentation/detection

Object detection or segmentation is one of the most attracting domains of computer vision, with a plethora of applications in several application areas such as medical [41,42], security [43,44], and surveillance [45,46]. Among these, medical is arguably the most prominent area for researchers to serve the humanity via computational intelligence techniques. In this survey, we consider segmentation/detection for WCE to automatically identify and localize any sort of abnormality. The basic flow of WCE segmentation and detection is given in Fig. 3(a), where input video frames are passed to the pre-processing step to remove noise and enhance the quality of frame. Then pre-processed frames are fed to the object detector module, where several steps are performed (varying from architecture to architecture) aimed to localize the so-called Region of Interests (RoI), namely, bleeding [47], different types of tumors [48], ulcers [49], and lesions [50]. To do this, several machine learning and deep learning methods have been introduced in the literature. Some of the famous deep learning architecture used for the detection and localization of these RoIs are Faster RCNN [51], MobileNet-V1, -V2 [52], FCN [53], and deeplab [54].

3.2. Redundancy removal/summarization

Redundancy removal and video summarization is a wide area of research with main focus on several fields of computer vision including surveillance [55–58], movies [59–61], and medical

Table 1
Detailed analysis and comparison of our study with existing surveys.

Surveys	Features					
	Year	Literature coverage	Number of reviewed papers	Existing surveys are reviewed	Datasets coverage	Main theme
[27]	2010	–	–	No	No	WCE imaging techniques with color and image processing AI tools
[28]	2012	2000–2009	18	No	No	Machine vision analysis for WCE videos
[29]	2013	–	34	No	No	Color image analysis of WCE videos
[30]	2015	–	–	No	No	Diagnosis of celiac disease using WCE
[31]	2017	2007–2016	40	No	No	Polyp detection and segmentation from WCE videos
[32]	2017	2003–2016	28	No	No	Polyp detection in WCE videos
[33]	2017	–	–	No	No	Localization and tracking of capsule in gastrointestinal tract
[34]	2018	2000–2016	–	No	No	Divided the methods into three types; preprocessing methods, real-time support at procedure time, and post-procedural applications
[35]	2019	2013–2019	15	No	Yes	Deep learning-based polyp recognition in WCE images and videos
[36]	2019	2003–2018	–	Yes	No	Deep learning-based feature extraction and fusion for abnormality detection in WCE videos
[37]	2019	2011–2017	9	No	No	Image compression techniques for WCE
[38]	2019	–	–	No	No	Machine learning and computer vision techniques for gastrointestinal endoscopy
[39]	2019	2003–2019	62	No	Yes	Tumor, polyp, and ulcer detection methods in WCE
[40]	2020	2016–2019	19	No	No	Deep learning-based methods for wireless capsule endoscopy
Ours	2020	**2010–2020**	41	**Yes**	**Yes**	WCE videos segmentation, redundancy removal/ summarization, classification/recognition, and personalization for smart healthcare

videos [7,62]. In WCE videos, the most tedious task for the medics is to watch hourly long videos. To assist them, several methods have been proposed in the recent literature aimed at summarizing the key visual information from these videos and thus, retain only those frames/video sequences, where any sort of abnormality is detected. The generic flow of redundancy removal and summarization is highlighted in Fig. 3(b). Analogously to other domains, the first basic step of summarization is pre-processing, which helps in enhancing the quality of frames for a better subsequent analysis. Then, the enhanced frames are forwarded to the feature extraction step, which extracts some patterns for dividing the video into a number of meaningful shots. Next, frames are selected from these shots with higher importance (referred to as "key frames" in related works), which are further combined to make a summarized video. The existing methods and models towards summarization and redundancy removal are based on both machine learning and deep learning, where the feature extraction and discriminator play as a backbone for each technique of shot segmentation, key frames selection, and summary generation.

3.3. Classification/recognition

Classification and recognition of different objects and events is a significant area of research for several applications, including disaster management [63,64], action and violence recognition [65–67], identity recognition and authentication [68,69], and medical images classification [70,71]. Recently, several classification paradigms have been suggested by the researchers based on both traditional machine learning and deep learning techniques. In our study, we provide a generic flow of WCE images classification given in Fig. 3(c), which includes the most essential steps, i.e., dataset preparation, image labeling into classes, preprocessing in the form of different color enhancement or noise removal, most importantly feature extraction, and learning of

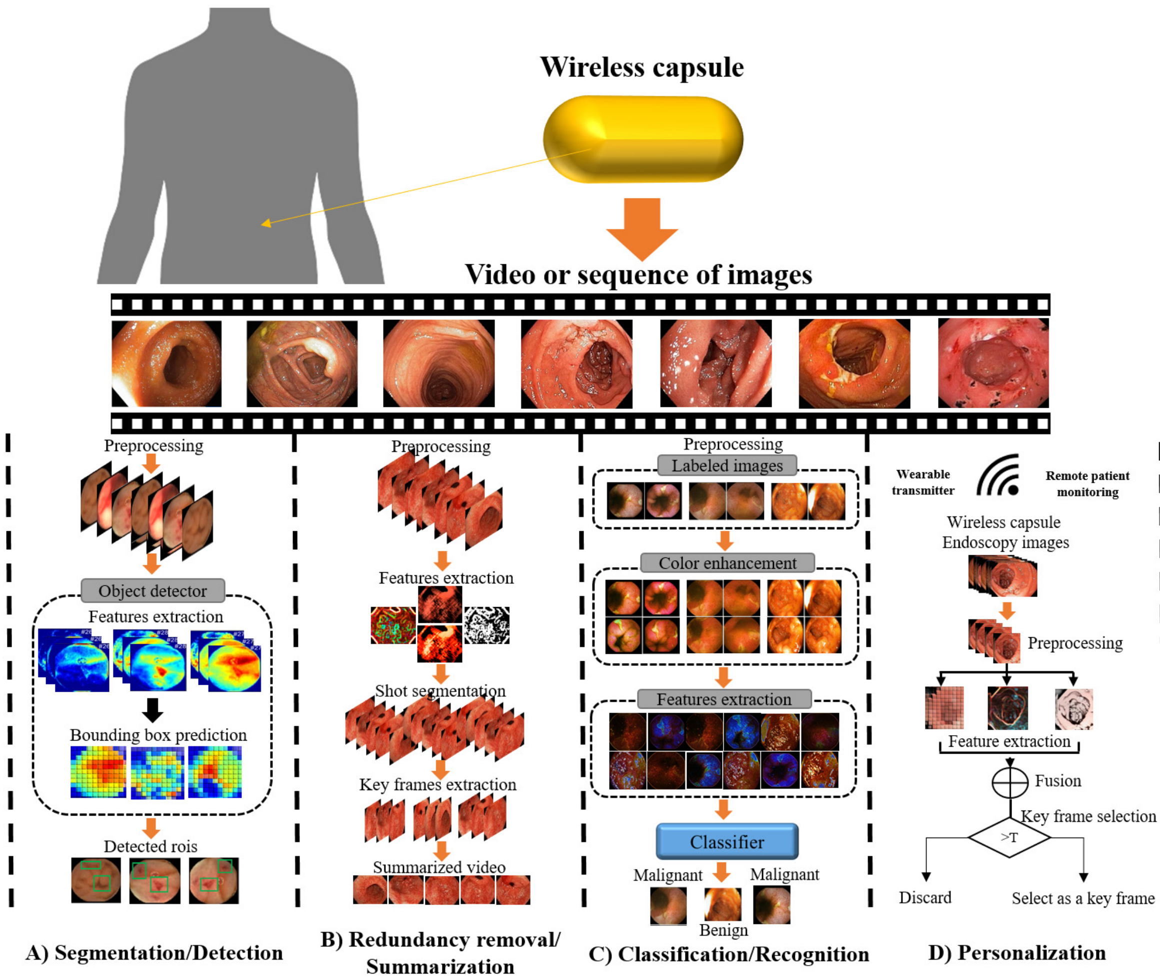

Fig. 3. Taxonomy of WCE images and video analytics into four different domains; (A) represents the generic flow of WCE segmentation or detection; (B) shows the procedure for WCE videos redundancy removal or summarization; (C) describes the steps for classification of WCE tumors; and (D) illustrates the key frames selection mechanism as personalization for WCE.

these features using a classifier to predict the final output. The final output depends upon two major factors; one is feature extraction and other is classifier. Due to the higher success of deep features in the literature almost, all of the recent methods are shifted to deep learning because of its deep structure and high-level semantic information extraction, mimicking the human brain that overrides the traditional way of handcrafted feature engineering.

3.4. Personalization

Due to the rapid development of smart sensors technologies, remote health monitoring has achieved an increasing importance in rural areas, as it facilitates the supervision and medical monitoring of patients without requiring to physically visit the hospital. In the current literature, several methods [72–74] have been proposed with the same aim to propose a system that is operational in both areas of cities and villages. Towards this end, we include a generic personalization scheme for WCE for key frames selection of remote patients as illustrated in Fig. 3(d), where the patient's WCE decoder module is directly connected to the cloud or any processing device (i.e., patient's smart phone), which processes the stream in nearly real-time. The main target of this personalization scheme is to discard the hourly long redundant information on the fly and store/disseminate details of interest to WCE process.

In a nutshell, the in-depth review of WCE videos/images processing methods published in the past eleven years (2010–2020) is summarized in Tables 2 and 3, respectively. In the review, we divided the methods into machine learning based (see Table 2) and deep learning based (see Table 3) techniques, where each method is explored for the given four domains with their short remarks to show the pros and cons of each method. The trend followed in the literature till date is that the methods proposed before 2018 are based on image processing or traditional machine learning techniques for all domains with the main aim to develop an automatic method that can generate a report without watching an hourly long video by the experts. The methods proposed in 2018 and afterwards are based on both machine learning and deep leaning based methods with some novel aspects to cope the pitfalls of previous methods. However, after a thorough survey, we observed that there are still several challenges/shortcomings that are not fully addressed in the literature of WCE images/videos analytics. For instance, the development of a hybrid yet intelligent framework that can work for all four domains specified in this study. Similarly, there is still a long way to control and properly trade off the capsule's brightness, its movement and size, efficiency, effectiveness, security, and overall AI-assisted decision-making towards personalization. All these challenges with future directions are covered in Section 5.

Table 2
Image processing and traditional machine learning based representative WCE methods in terms of segmentation, redundancy removal, summarization, and personalization with their strengths and weaknesses. Based on this perspective, both industry and academia can follow appropriate paths towards smart healthcare, considering their constraints in terms of personalization, cost, efficiency, and privacy/security.

Ref	Segmentation/ Detection	Summarization/ Redundancy removal	Classification/ Recognition	Personalization	Remarks
[75] (2010)	×	✓ (Sift Flow algorithm, Histogram of Sift Flow Direction and Sift descriptor are used)	×	×	• This method focuses on endoluminal aligning and sequence through motion structure of the intestine in WCE. • They merge three different types of descriptors to select the high rank frame in WCE videos.
[76] (2010)	×	✓	✓ (unsupervised mining of video frames)	×	• This method is based on a data reduction algorithm for WCE. • Their method emphases on both redundancy removal and summarization.
[77] (2010)	×	×	✓	×	• Distributed processing approach for endoscopy video summarization. • No focus on redundancy removal and personalization.
[78] (2011)	✓ (Log Gabor filter is used for segmentation)	×	✓	×	• An automatic approach for discovering protrusion in WCE video frames. • There is no mechanism for redundancy removal and personalization.
[79] (2011)	✓ (Probabilistic Neural Network (PNN))	×	✓ (The WCE images are classified into bleeding and non-bleeding group)	×	• A novel and intelligent Probabilistic Neural Network (PNN) for bleeding detection in WCE images.
[80] (2012)	✓ (SURF, Bag-of-visual and K-means and SVM are used)	×	✓	×	• SURF features are extracted where bag-of-visual are constructed using K-mean. • SVM classifier on these feature vectors to detect Polyp in the WCE images.
[81] (2012)	✓ (Textural features, sequential floating selection and SVM-based feature selection)	×	✓ (SVM is used to classify the tumor)	×	• Local binary pattern and wavelet features are extracted. • SVM classifier is used to classify these features for tumor recognition in WCE images.
[82] (2013)	×	✓ (Combination of intensity correction and optical flow)	×	×	• Their mechanism only focuses on redundancy reduction in WCE. •Optical flow needs more processing, thus, its chances for personalized WCE is limited.
[4] (2014)	×	✓ (Jeffrey-divergence (JD) and inter-frame correlation of color channels based on Boolean series)	✓	✓	• This method presents a resource- and bandwidth-aware video summarization. • The summarization pipeline is divided into two steps: reducing redundancy using patient's smartphone and classification of non-redundant frames into non-informative and informative using cloud service. • Suitable option for personalized WCE with major role in smart healthcare industry.
[72] (2014)	×	×	✓ (Saliency map based keyframes selection)	✓	• This method selects semantically relevant video frames from WCE data considering gastroenterologists' perspective. • Saliency map is used to select keyframes. • Cloud services and their integration with mobile computing for WCE, is missing, restricting its usefulness to healthcare.
[83] (2015)	✓ (Normalized Gray Level Co-occurrence Matrix (NGLCM) features with SVM are utilized)	×	✓ (SVM is used for classification)	×	• A novel method for GI hemorrhage detection using WCE images.
[84] (2015)	×	×	✓ (Partitioning of frame into homogeneous categories based on visual and temporal descriptors)	×	• It finds the optimal relevance weight of features within a cluster. • Further, it finds optimal number of clusters in an unsupervised way. • The final summary consists of frames with all the clusters after discarding noisy frames.

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Table 2 (*continued*).

Ref	Segmentation/ Detection	Summarization/ Redundancy removal	Classification/ Recognition	Personalization	Remarks
[85] (2015)	✓ (Saliency Based Ulcer is used for detection)	×	✓ (Bag-of-Words (BoW) or BoF model to classify the ulcer images)	×	• A computer-aided system is proposed to detect ulcer in WCE images. • At first, a saliency method based on multi-level super pixel, is proposed. • The saliency is evaluated based on color and texture features. • The output saliency maps are fused to obtain final saliency map.
[86] (2015)	×	×	✓ (Class Means Cosine Similarity distance for similar frames removal)	×	• Low-level features are used for preprocessing of WCE image bleeding classification algorithm. • Image sequence reduction and summarization. • The mechanism presented is simple with no convincing mechanism for redundancy removal.
[87] (2016)	(K-mean and SVM with color textures for bleeding detection)	×	✓ (KNN classifier is used)	×	• K-mean and SVM are used for bleeding detection in the WCE images.
[88] (2016)	×	✓ (Shot segmentation through linear SVM classifier)	✓ (Key frames extraction via adaptive K-means clustering)	×	• SVM classifier for shot boundary detection and similar frames selection. • Siamese network and SVM classifier are trained on the same data of similar and dissimilar frames of WCE.
[73] (2016)	×	✓	✓	✓	• The problem of secure transmission of WCE data is considered. • Three-level encryption algorithm for secure transmission of keyframes. • No focus on visual attention for the WCE images while selecting keyframes. • The security method presented is not efficient enough for real-time WCE.
[89] (2017)	✓	×	✓	×	• Two dimensional digitized images are pluralized to prune them for the detection of polyps in endoscopy images.
[90] (2017)	×	✓	✓	✓	• Summarization based on fusion of curvature, inertia, and multi-scale contrast. • Secure cryptosystem for secure transmission of extracted keyframes. • It has fixed block size, which can be made adaptive. • Ability for secure and personalized WCE in healthcare
[91] (2018)	✓	×	✓	×	• Based on computer-aided method, the small intestinal ulcer and erosion in wireless are detected in capsule endoscopy.
[92] (2018)	✓	×	✓ (Support vector machine is used)	×	• The animal paws are tracked through segmentation and the segmented parts are classified using SVM. • The objects are classified using kinematic features of running animals.
[93] (2018)	✓ (Local binary pattern and discrete wavelet transform (LBPV) is used)	✓ (LBPV descriptor is used to summarize the global and local densities)	✓ (SVM)	×	• The abnormalities detection process in WCE images is made automated through texture extraction scheme for polyp and pathological inflammation.
[47] (2019)	✓ (automatic multiple bleeding spots detection)	×	×	×	• Their method relies on two main factors: (1) color feature extraction from multiple bleeding spots and (2) recognition through both supervised and unsupervised learning techniques.
[94] (2019)	×	✓ (Redundant frames removal)	×	×	• Firstly, similar frames are detected using skip prediction algorithm. • Next, corner is detected using RANSAC combined with Harris algorithm.
[48] (2019)	✓ (Small bowel tumors detection using Accelerated EM Algorithm)	×	✓	×	• In the first step, normal and abnormal tissues are separated using GMM. • Next, a network is trained for both classification and segmentation using CIELab color features.

(*continued on next page*)

Table 2 (*continued*).

Ref	Segmentation/ Detection	Summarization/ Redundancy removal	Classification/ Recognition	Personalization	Remarks
[95] (2019)	×	×	✓ (Ulcer detection)	×	• The features used for ulcer detection are G component from RGB, and Cr component of YCbCr color spaces, respectively. • After feature extraction, SVM classifier is used for ulcer recognition.
[96] (2020)	×	✓ (Structure similarity based key frames selection)	×	×	• A hierarchical clustering based algorithm is applied to HSV color space for key frames extraction.
[74] (2020)	×	×	✓ (colorectal cancer detection)	✓	• A fluorescence imaging based method is presented to recognize the colorectal cancer in GI tract.

Table 3
Deep learning-based WCE methods in terms of segmentation, redundancy removal, summarization, and personalization with their strengths and weaknesses.

Ref	Segmentation/ Detection	Summarization/ Redundancy removal	Classification / Recognition	Personalization	Remarks
[97] (2018)	✓ (CNN for hookworm detection)	×	✓	×	• Hookworms are detected in the WCE images using CNN approach.
[98] (2018)	✓ (MLP structures with fully connected layers followed by softmax layer)	×	×	×	• Investigation of simplification of neural networks for automatic bleeding regions detection in WCE data. • No focus on summarization of WCE videos • No consideration for personalization
[10] 2018	✓ (Tubular regions are detected using a CNN)	×	×	×	• The aim of this work is hookworm detection using deep learning. • Tubular regions are detected using a CNN, followed by hookworm classification via another CNN. • No focus on redundancy removal and summarization. • Personalization of this approach is difficult as their framework is using two CNNs and the running time cannot meet real-time WCE, needed for smart healthcare.
[99] (2019)	×	×	✓ (Ulcer detection in WCE images using CNN)	×	• Their main focus is on detection of ulcer in WCE video frames using the transfer learning strategy of existing state-of-the-art CNNs. • No mechanism for ulcer localization.
[100] (2019)	×	×	✓ (Classification of different types of tumors)	×	• Deep learning with triplet loss function to improve the generalization of the model for WCE images. • Their main concern is development of a generic method that is adoptable to all kind of WCE images/videos datasets.
[101] (2019)	✓ (CNN with transfer learning and cascade proposal are used to localize abnormal patterns)	×	×	×	• This method is based on four different building blocks including an end-to-end deep cascade network, multiregional combination, dense region fusion, and negative category with transfer learning.
[49] (2019)	✓ (CNN based Ulcer localization in a large WCE dataset)	×	×	×	• They proposed a deep CNN based ulcer detection architecture called Second Glance. • Their architecture consists of two blocks: one is patch-level refinement and other is full image refinement for accurate detection.
[102] (2019)	✓ (Deep CNN based erosions and ulcerations detection)	×	×	×	• A single shot multibox detector based CNN architecture is trained for automatic detection of erosions and ulcerations in WCE videos.
[103] (2019)	×	×	✓ (Lesion classification using custom CNN architecture)	×	• A custom CNN architecture is designed for the classification of lesion inside WCE videos.

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4. Benchmark WCE datasets

In the current literature of WCE, several datasets have been contributed with available ground truth for different purposes i.e., summarization, segmentation, tracking, and personalization. In many cases, the WCE data is not available to the research community as in other medical domain due to the requirement to maintain the privacy of patients. In this section, we enumerate

Table 3 (*continued*).

Ref	Segmentation/ Detection	Summarization/ Redundancy removal	Classification / Recognition	Personalization	Remarks
[104] (2020)	×	✓ (Summarization and enhancement of WCE videos)	×	×	• Two types of features are extracted from the input video: color features and deep features using ResNet50. • Both of these features are passed to SVM classifier followed by SVD analysis for final key frames selection.
[50] (2020)	✓ (Detection and classification of protruding lesions)	×	✓	×	• A hybrid detection and classification algorithm is proposed for protruding lesions in WCE videos. • The experiments are performed on 30,584 WCE images collected from 292 patients.
[105] (2020)	×	×	✓ (Deep CNN based bleeding classification)	×	• Investigates different machine learning and deep leaning based methods for the classification of bleeding inside WCE videos.
[106] (2020)	✓ (Small-bowel angioectasia detection using CNN)	×	×	×	• A single shot multibox CNN based detector is trained over 2237 WCE angioectasia images for accurate detection of small-bowel angioectasia.

Table 4
Important details about publicly available WCE datasets.

Dataset	Features					
	Ref	Number of images	Number of videos	Ground truth available?	Domain	Resolution
KID images Datasets	[107,108]	2448	–	Yes (abnormal areas are annotated)	Segmentation/Detection	360 × 360
KID videos Dataset	[108,109]	–	6	Not available	Not specified	360 × 360
MICCAI Gastroscopy Challenge Dataset	[110]	10,000	–	Yes (divided into classes)	Classification/summarization	768 × 576
Capsule endoscope tracking dataset	[111]	–	117	Yes	Tracking GI tract	576 × 576
Gastrolab	[13]	Not specified	Not specified	Partially	Classification/summarization	Varying

and briefly comment on the publicly available datasets for WCE, consisting of both WCE images and videos with ground truth. Details about these datasets are given in Table 4.

4.1. KID images dataset 1 and 2 [107,108]

KID is a non-profit, open access database of WCE images and videos with high-quality annotation. This database is specially created for the research purposes of clinicians and educational sectors towards the improvement of CAD systems for WCE. There are two KID image datasets released in 2014 and 2018, respectively. The first KID image dataset [107] consists of 77 high quality WCE images captured by using MiroCam® developed by IntroMedic Co, Seoul, Korea. The main task defined for these images is to detect and segment different types of abnormalities inside human's GI tract, including apthae, angioectasias, polypoid lesions, chylous cysts, villous edema, stenosis, bleeding, lymphangiectasias, and ulcers. The most recent KID image dataset [108] comprises 2371 WCE samples that include both normal and abnormal images of stomach, esophagus, and small bowel. The abnormalities covered in these images are polypoid, vascular, and inflammatory lesions.

4.2. KID videos dataset 1, 2, and 3 [108,109]

KID videos dataset is the combination of three different videos datasets proposed in 2015, 2015, and 2018, respectively. All these videos are created by a MiroCam® (IntroMedic Co, Seoul, Korea) capsule endoscope, and is available for the research community without ground truth or annotation. These datasets are often used for all domains of WCE analytics.

4.3. MICCAI gastroscopy challenge dataset [110]

Medical Image Computing and Computer-Assisted Intervention (MICCAI) is a WCE dataset that includes images from different parts of the gastroscopic tract. This dataset was specially proposed for the MICCAI challenge that took place in Munich, Germany, in 2015. The challenge was given to researchers for correctly classifying the abnormalities in gastroscopic images. This dataset comprises 10,000 images, collected from 544 normal candy stripers and 519 patients with several abnormalities, i.e., cancer, gastric ulcer, bleeding, and gastritis. In the challenge, they also provided a specific subset of 205 normal and 260 abnormal images for training set, while 104 normal and 129 abnormal WCE images were considered as testing set.

4.4. Capsule endoscope tracking dataset [111]

This dataset includes a total of 117 WCE videos, each with a duration of approximately 20 s. The original videos are collected from the "Given Imaging Atlas database", where no annotation is provided. Interestingly, the main contribution of this dataset was the fact that it resulted from the annotation of an existing dataset for capsule endoscope tracking and transformation estimation for abnormality detection and classification.

4.5. Gastrolab [13]

Gastrolab is a large endoscope images and videos database, consisting of both traditional and wireless endoscope videos. This site has been developed since 1996 to provide services for treatment guidelines and diagnostic services. This database has been used by different research works reported for WCE videos summarization, tumor segmentation, and recognition.

5. Challenges, recommendations and future research directions

In this section, we will cover all the major challenges with future directions of WCE images/videos analytics as concluded after a thorough survey in Section 3. As stated earlier, a significant research is going on in the field of WCE images/video analytics in terms of segmentation, lesions detection, redundancy removal, and summarization. However, these efforts alone are not enough for a smooth integration of state-of-the-art methods for practical smart healthcare services, especially for those deployed over remote areas with limited hospitals and medical centers. Thus, further smart and efficient mechanisms for WCE are still to be proposed, which can make a larger portion of population leverage their advantages [112]. In this perspective, we highlight several challenges in WCE, which need to be deeply investigated to move a step forward towards smart healthcare.

5.1. Automatic brightness adjustment

The first challenge included in our prospects is the "*automatic brightness adjustment*" of the WCE images when the capsule is passing through the GI track. In practice, it has been observed that certain frames are over-illuminated or under-illuminated, thus affecting the subsequent segmentation, summarization, and/or classification tasks for WCE videos [113,114]. Therefore, the adjustment of brightness is a crucial step towards accurate diagnosis as the remaining procedures along each workflow of Fig. 3 are dependent on the visual information captured by the capsule. In addition, the time complexity of this brightness adjustment algorithm can set another hurdle towards making e-health of practical use. Consequently, adaptive brightness adjustment mechanisms need to be designed to keep the running time to the minimum.

To cope with this challenge, similar works have been proposed in the literature. For instance, Shrestha et al. [9] presented an automatic brightness adjustment mechanism using image segmentation (where the image is segmented into four brightness levels and regions) and followed by sigmoid function for finding the optimized brightness. In another method, Shrestha et al. [115] proposed an adaptive illumination based on the brightness of embedded LEDs inside WCE. Van Vliet et al. [116] presented a hybrid brightness and hue stabilization method based on color features analysis. However, due to limited performance and adjustment of different lighting conditions, there is still a long way to come up with automatic and adaptive brightness adjustment mechanisms.

5.2. Controlling the capsule's movement

The second major challenge identified from our literature assessment is "*controlling the capsule's movement*" as per the clinician's choice to visualize areas of interest for a deeper inspection of certain diseases. Here "movement control" refers to the capsule's speed, orientation, and position; each has its role in the overall WCE procedure, and none of them can be ignored. In this direction, several attempts have been made. For instance, Geng et al. [117] achieved millimeter-level accuracy for capsule's localization using a hybrid approach of radio frequency and image processing. Gao et al. [118] presented a motor-based capsule robot with a wirelessly controlling process for power transmission. Fontana et al. [119] contributed a new spherical-shaped capsule for screening of colorectal cancer with supporting modules of control, actuation, localization, and a battery with recharging circuit. The demo system was developed using FFGA, showing a reduction in the friction of the capsule during its locomotion, ultimately leading to a better patient's acceptability. However, the capsule captures images at 320 × 320 with 1.5 frames per second (fps) and is computationally complex. Thus, its design needs to be improved further so as to be recommended for clinical practice in WCE. Than et al. [120] presented a tracking method for localizing robotic endoscopic capsules using a rigid body transformation. However, their target is the corpus of patients under observation in hospitals and is thus not feasible for smart healthcare.

More recently, Duan et al. [121] used magnetic field theory to place a capsule endoscope at a desired area with a controlled orientation. Alsunaydih et al. [122] presented a locomotion approach via a dynamic electromagnetic field for controlling the motion of capsule. Aghanouri et al. [123] presented a high-level control system for active capsule endoscope, which can suggest planning path for the capsule, when the shape and size of the stomach cannot be exactly determined. Xie et al. [124] proposed magnetically guided capsule endoscopy but their focus is only pediatric patients having abdominal pain and thus not generalize for personalized WCE. Towards controlling the movement of capsule there is a long way, but it can be possible by adopting activity recognition algorithms [125–128] to tracking and recognizing GI tract.

5.3. Capsule's size in GI tract: Implications in power and movement dynamics

The movement of capsule is a challenging problem due to several obstacles along its trajectory. Among all related factors, the capsule's size restricts the operation of multiple functionalities of the capsule such as image capturing, movement, power management, and communication. Similarly, the GI tract is smooth yet has irregularities, which makes the development of an effective movement mechanism difficult to accomplish in practice. In addition, movement control includes different functions for which more motive power is needed. Although Zhang et al. [129] recently disclosed an adaptive frame rate control mechanism for wireless capsule, the other supporting modules consume even more power, thus limiting the overall feasibility for clinical practice and personalization.

Furthermore, the size and movement of the cupules are utilized for the autonomous navigation, pressure monitoring, and 3D reconstruction of lesions regions. Towards navigation, Alsunaydih et al. [130] proposed a navigation method for both ordinary and wireless endoscopies by taking care of capsule and movement even in a dark or liquid environment (i.e., mucosa). More recently, another method presented by Nam et al. [131] stated the influence of size with other factors for small bowel 3D reconstruction using stereo camera. But, there is still road ahead in terms of meeting feasible tradeoffs between the dimensions of the capsule, its manageability through the GI tract, and the power consumption of its embedded modules and functionalities.

5.4. Ensuring the security, smartness and energy efficiency

Another challenge is "*ensuring the security, smartness, and energy efficiency*" of the WCE as a general guideline for Internet of Medical Things (IoMT), which is globally accepted by e-health community [24,132]. The basic aspects for an IoT medical sensor are recently recommended by [132] and visually conceptualized in Fig. 4. Specifically, this figure illustrates the balance between energy efficiency, intelligence, and security to be met by WCE, along with technologies that can help improving each of these design goals.

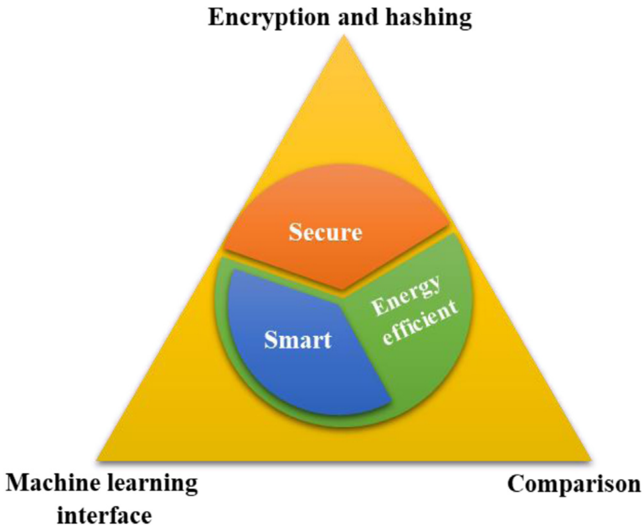

Fig. 4. Basic aspects of IoT sensors, recommended by e-health community.

The necessity of ensuring these requirements increases when a medical procedure includes cloud computing platforms and the diagnostic process demands real-time observation, as it occurs in WCE. In this direction, some studies are already conducted with focus on individual requirement given in Fig. 4. To comment on an exemplary few, Mehmood et al. [72] presented a video summarization-assisted tele-endoscopy using handcrafted features for efficient handling of the WCE data. In a follow-up work [4], they presented a resource-aware system that adaptively offloads the complex processing to the Cloud, considering the resources of patient's smartphone, leading to a preliminary attempt at personalized WCE. Focusing on another aspect of WCE, Muhammad et al. [73] highlighted the application of steganography for secure WCE by presenting a detailed use case. More recently, Hamza et al. [90,133] exploited encryption approaches for the keyframes extracted by an AI algorithm for their secure transmission to hospitals or remote gastroenterologists, contributing to both personalization and security. Summarizing these attempts, it has been observed that their focus is only on a subset of these aspects, as the accomplishment of all requirements in terms of security, smartness and energy efficiency is challenging by itself due to their conflicting nature. Thus, significant efforts are needed to propose novel frameworks for smart, secure, and personalized WCE by exploring lightweight CNNs with federated learning and image hashing strategies, instead of time-consuming feature engineering, local learning models and encryption approaches, respectively [56,134].

5.5. Explaining decisions made by intelligent computational methods in WCE

Last but not the least, we emphasize on the increasing concern of the medical experts with the irruption and proliferation of intelligent Artificial Intelligence method in traditional medical diagnosis and treatment processes [135,136]. WCE is not an exception to this statement: specialists are reluctant to make decisions (such as the prescription of a medical treatment or an invasive surgery) solely on the output of computational methods for any of the tasks defined in our taxonomy. Indeed, extended information should be provided along with the model's output that could explain the output of the model in regard to its input or the procedure followed by the model to predict the input imagery. This paradigm is of even higher relevance when bearing in mind the dominance of black box learning models in computational tasks formulated within each domain of our taxonomy (e.g. detection/segmentation), particularly those belonging to the branch of Deep Learning. All techniques devised to explain decisions made by opaque Artificial Intelligence methods are collectively known in the current literature as eXplainable Artificial Intelligence (XAI) [137–139]. We advocate for a closer look to be paid at this crucial aspect in the near future, for medical experts to validate and trust practical WCE systems endowed with AI methods. In particular we foresee great opportunities for the specific branch of post-hoc explainability techniques for Deep Learning models, which provide understandable explanatory information about the information learned by convolutional and recurrent neural layers. Unless more efforts are invested in this direction, advances in Artificial Intelligence methods suited to deal with problems related to WCE will remain far from yielding practical value.

6. Concluding remarks

WCE is a recent technology that has several advantages such as efficiency, accuracy, and high-level of adaptability when compared to traditional endoscopy visualization techniques. WCE was introduced in 2000 and approved in 2001. Ever since, this research area is still significantly less explored by computer vision experts than other fields related to medical imaging. To drive the attention of researchers towards this topic, in this compact review paper we have presented and critically examined the related literature in a comprehensive manner, along with future research guidelines. Firstly, we have overviewed existing WCE surveys and compared them with the current study using several metrics including literature coverage, number of papers, and coverage of existing surveys and datasets with main theme. Next, we reviewed recently reported WCE techniques on the basis of their main pipeline and supported the generalized flow with references from the related literature. Following this, we discussed the publicly available datasets used in this domain, irrespectively of the purpose such as summarization, segmentation, and/or personalization. Finally, we discussed the challenges faced in WCE domain with their possible solutions, among which we highlight the need for coupling power consumption, learning/image processing and explainability of automated decisions in a more integral fashion. For this to occur, research directions such as energy-efficient designs of functionalities involved in WCE, XAI techniques for image-based Deep Learning methods, and privacy-preserving system architectures are among our identified prospects for the future of this field.

WCE is an emerging area that comprise several processes, each of sensitive nature that demands sophisticated technologies for an in-depth understanding of the information captured by the capsule. Reported improvements supported by both conventional and deep learning methods and personalization have the potential to support healthcare services at a large scale, which has hitherto propelled a remarkable number of research contributions summarized in this overview. We believe that our recommended directions will support the ongoing research efforts in this domain and will serve as a reference material for newcomers joining this vibrant area of research.

CRediT authorship contribution statement

Khan Muhammad: Conceptualization, Methodology, Software, Writing - original draft, Project administration. **Salman Khan:** Conceptualization, Formal analysis, Writing - review & editing. **Neeraj Kumar:** Formal analysis, Investigation, Validation, Writing - review & editing. **Javier Del Ser:** Investigation, Validation, Writing - review & editing. **Seyedali Mirjalili:** Investigation, Validation, Writing - review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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