International Journal of Cognitive Computing in Engineering 2 (2021) 83–92

Contents lists available at ScienceDirect

International Journal of Cognitive Computing in Engineering

journal homepage: www.elsevier.com/locate/ijcce

A survey on deep learning models for wireless capsule endoscopy image analysis

Prabhananthakumar Muruganantham, Senthil Murugan Balakrishnan*

School of Information Technology and Engineering, VIT University, Vellore, Tamil Nadu, India

A R T I C L E I N F O

Keywords:
Wireless Capsule Endoscopy (WCE)
Deep Models (DM)
Convolutional Neural Network (CNN)
Generative Adversarial Network (GAN)

A B S T R A C T

Abdomen Bleeding, Ulcer, Tumour, Crohn's disease, Celiac disease and other diseases in the gastrointestinal tract (GI) are difficult to diagnose, due to the inescapable inherent difficulty in accessing a volute setting in the human body. Wireless Capsule Endoscopy (WCE) offers a patient-cordial, non-invasive and painless investigation in the GI tract. Automatic detection of anomalies in WCE images using Deep Learning Models improves the detection accuracy but it requires a huge number of labeled data for model training. But these deep models suffer from explain-ability and fail to include expert knowledge in the model decision-making process. By keeping these aspects in mind, this survey aims to identify the opportunities for using Semi-Supervised deep learning models over supervised deep learning methods in Wireless Capsule Endoscopy (WCE) anomaly detection and classification. This paper presents a comprehensive survey on various deep learning solutions for anomaly detection and localization techniques utilized in WCE images in the aspect of performance, complexity, and the quality of the dataset. The survey outlined the proposed Attention and Domain Assisted Generative Adversarial Network (ADA-GAN) based Semi-Supervised Model for WCE anomaly image classification along with initial results. The result derives the shortcomings of the current literature methods and paves the potential research opportunities in the Semi-Supervised models in Wireless capsule endoscopy image analysis.

1. Introduction:

Wireless Capsule Endoscopy (WCE) is a non-invasive technique used to detect anomalies in the Human Gastrointestinal (GI) tract. It is a capsule-shaped object with a length of 26 mm by 11 mm in diameter, consisting of an optical dome, illuminator, imaging sensor, battery and RF transmitter. In the evaluation process, the patient swallows the WCE and then moves it through the diminutive intestine slowly and while moving, it takes pictures of the entire GI tract (Ciuti, G., et al. 2011). Conclusively, these images are transmitted using a wireless technique to a data-recording contrivance for medicos to examine the images later for diagnosis. As on average, 50k to 60k pictures are captured whilst traveling through the GI tract. The medico needs to verify all the 60k pictures to detect any abnormality present in the GI tract, it is a time-consuming and tedious process. As the video is of a length that is equal to the time taken for the capsule to travel through the intestines, the medico is likely to miss an important frame that has the abnormality featured. Hence, Computer-Aided Detection (CAD) methods were proposed to overcome the current practices. The common abnormalities such as polyp, tumor, ulcer, celiac, and bleeding were found in the GI tract are shown in Fig. 1. Many researchers have targeted bleeding detection in WCE images (Fu, Y., et al. 2014; Ghosh, T., et al. 2018; Sainju, S., et al. 2014; Schurischuster, S., et al. 2018; Xing, X., et al. 2019). On the other hand, researchers use various methods to detect a single abnormality like polyp, ulcer and celiac (Aoki, T., et al. 2018; Gadermayr, M., et al. 2018; He, J., et al. 2018; Leenhardt, R., et al. 2019). Localization of the abnormality within WCE images was addressed to many abnormality detection methods (Guo, X., et al. 2020; Koulaouzidis, A., et al. 2018).

Computer-Aided abnormality detection in capsule endoscopy images has opened a greater research avenue in the area of medical image processing and machine learning (Liedlgruber, M., et al. 2011; Guerrero Sánchez, Y., et al. 2020; Gao, W., Günerhan, H., & Baskonus, H. M. 2020). To identify and detect abnormalities present with different color and texture patterns, various algorithms such as image processing, Deep Learning, and machine learning are used (Ciuti, G., et al. 2011). Machine Learning uses the methods of super-pixel segmentation, Salient Detection, Visual words, and Bag of features to learn abnormalities using the handcrafted features, such as Texture, color, and Statistical features (Yuan, Y., et al. 2017; Yuan, Y., et al. 2016; Xing, X., et al. 2019; Sivakumar, P., et al. 2019; Charfi, S., et al. 2020). The performance of the Machine Learning based models relies on the features that are used to represent the anomalies and the methods used to extract the features from images (Pogorelov, K., et al. 2017; Charfi, S., et al. 2020). Deep learning models use labeled datasets to learn features to detect abnor-

* Corresponding author.
E-mail addresses: prabhananthakumar.m@vit.ac.in (P. Muruganantham), senthilmurugan.b@vit.ac.in (S.M. Balakrishnan).

https://doi.org/10.1016/j.ijcce.2021.04.002
Received 24 February 2021; Received in revised form 13 April 2021; Accepted 24 April 2021

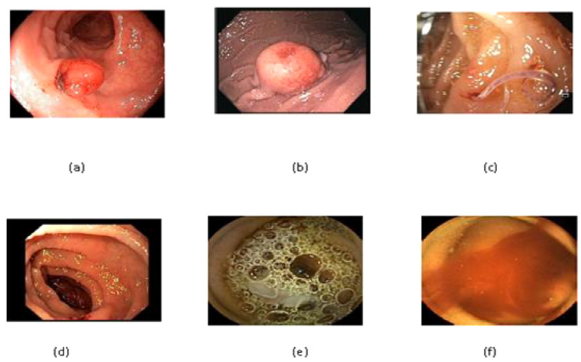

Fig. 1. (a) Polyp, (b) Tumour (c) Hookworm (d) Celiac (e) Bubbles (f) Bleeding

malities. Deep models like CNN models have achieved great success but it depends on the quality of the dataset, in the medical domain inadequate labeled dataset remains a major issue in this area (Litjens, G., et al. 2017). To overcome this issue researchers started thinking about semi-supervised learning and expert knowledge incorporation into deep models to develop clinical trusted deep models (Jia, X., et al. 2020). Over the past few years, many reviews have been made in computer-aided detection and classification in endoscopy image analysis in deep model architecture, performance, computational complexity and features used for anomaly representation. In recent years, improvements have made in Computer vision using deep models such as attention mechanisms, expert knowledge inclusion in the model decision-making process and generative deep model architecture. To identify the new research gaps in other aspects, this paper proposes a survey on deep models in WCE images considers by excluding the handcrafted features and classification methods (SVM, K-NN and Random Forest).

The rest of the paper is organized as follows, Sec. 2 gives a detailed explanation about various survives published in the domain of deep models in Capsule Endoscopy image analysis and Medical Image Analysis. Sec. 3 explains the motivation behind this review and the aspect of the review. Sec 4 illustrates a detailed survey of various deep learning-based solutions published in the domain of WCE image analysis. Sec 5 highlights the research findings of this detailed survey. Sec 6 describes the proposed semi-supervised GAN for WCE image classification. Finally, Sec. 7 concludes and brings out the foreseeable enhancements.

2. Related work

For the past two decades, in the domain of WCE image analysis, only limited number review has been carried out with the focus on the model architectures and it is performance. Most of the survey concerns about various features to represent anomaly pattern and classifiers used for classification (Trasolini, R., et al. 2021, Rahim, T., et al. 2020 & Muhammad, K., et al. 2020). This paper confines recently published reviews in WCE image analysis and medical image analysis. To collect more insights, the survey also includes the works of literature published in general medical image analysis to infer more detailed information about the application of deep learning models.

In the domain of WCE image analysis, Ali, H., et al. (2019) conducted a detailed survey on many computer-aided detection methods. Various endoscopic procedures were precisely described and color, texture feature extraction methods in spatial, geometric and frequency domain are analyzed. Moreover, the survey considers different deep learning models published for WCE image analyses were discussed and also lists the publicly available datasets. Also, the survey makes very clear that the literature was not catering to the quality of the dataset or dataset class imbalance and model trustworthy in their analysis.

Sreekutty, K., & Hrudya, K. P. (2017) have reviewed few articles published to detect the abnormality in the WCE domain. The review mainly discusses the color, texture, statistical and shape features. The feature extraction methods with their performance, advantages and disadvantages were also described.

Liedlgruber, M., & Uhl, A. (2011) surveyed the articles proposed for Endoscopic computer-aided detection. Several commonly used features in the domain of medical processing such as spatial domain, frequency domain and high-level features were discussed. The survey compares the performance of SVM and k-NN classifiers and also describes the future research directions.

Du, W., et al. (2019) reviewed the recent pieces of literature on Deep Learning based abnormality detection in various endoscopy procedures (Colonoscopy, Gastroscopy and WCE). Deep learning models were categorized according to the task and purpose of the WCE image analysis in Detecting, Classifying and Segmenting domains. LeNet, AlexNet, GoogLeNet, VGGNet, ResNet, R-CNN, FCN, SegNet and DeepLab were the models contributing to endoscopy image analysis were discussed along with their performance analysis. The author concluded the review by highlighting the significant domains of the 3D-CNN-based DL diagnostics system, Real-time video processing and the Development of RNN and GNN.

Jia, X., et al. (2020) have reviewed several handcrafted-based feature selection literature and deep learning-based feature selection solutions proposed for polyp screening in WCE image Analysis. Many unsolved challenges in deep learning methods in WCE image analysis were discussed and the conclusion highlights future research direction.

A survey made by Park, J., et al. (2019) describes various computer vision-based post procedures like image enhancement, depth sensing and accurate localization of capsules in the GI tract. The review of the literature concentrated the discussion on the possibility of using DL models in WCE image analysis. The survey compares the works of literature in terms of the architecture and the performance of DL in WCE image analysis. Moreover, the survey identifies that no literature addresses the dataset issues and model trustworthy issues in deep learning models in WCE image analysis.

This survey boundary was extended to general medical image analysis using DL models and needs to review the following few pieces of literature in general medical image analysis to offer more information to adopt the concepts from other medical image modalities

Litjens, G., et al. (2017) reviewed and summarized over 300 articles for deep learning in medical image analysis. This review article is marked as significant in that it completely covers and focuses on all the medical applications along with DL methods. Various supervised deep architectures (CNN, RNN, Multistream CNN) and unsupervised deep architectures (Auto Encoders, Restricted Boltzmann machine, Generative Adversarial Networks) were discussed under classification, segmentation and detection tasks. Also, the DL contributions to various anatomical areas (Brain, Eye and Chest) and their performance in the publicly available dataset were discussed. At the end of the review, the importance of DL in medical image analysis and further research direction in the aspect of insufficient labeled dataset and class imbalance is highlighted.

Chebli, A., Djebbar, A., & Marouani, H. F. (2019) proposed the first semi-supervised learning in medical image analysis. The author reviewed various semi-supervised based CAD literature for medical image analysis using the following category generative models, self-training models, co-training models, Transductive SVM and Graph-based Models. Also, the importance of an insufficient labeled dataset in medical image analysis was discussed. Zhou, T., Ruan, S., & Canu, S. (2019) completely reviewed various deep learning architectures for multi-modality medical image segmentation tasks. Image Fusion at the input level, Layer level and decision level were discussed.

Review literature on Deep learning models for medical image analysis considered for reviewing, didn't focus on dataset quality (size, class balance and labeling) and model trustworthiness but all the reviews focus on the Deep model architectures and their performance. Without the benchmark dataset and standard evaluation metrics for deep

Table 1
Existing Review Articles in WCE image analysis in the aspect of DMA (Deep Model Architecture), DMP(Deep Model Performance), DMT(Deep Model Trustworthiness), DQ(Dataset Quality), DKDM(Domain Knowledge Inclusion in Deep Models)

Review Articles	Description	DMA	DMP	DMT	DQ	DKDM
Ali, H., et al. (2019)	Survey on Various Computer-Aided Detection Method in WCE image	√	√			
Sreekutty, K., et al. (2017)	Survey on Anomaly Detection in WCE images	√	√			
Liedlgruber, M., et al. (2011)	Survey on Computed Aided Detection in Endoscopic Images	√	√			
Du, W., et al. (2019)	Deep Learning based on Anomaly Detection in Endoscopic Images	√	√			
Litjens, G., et al. (2017)	Survey on Deep Learning Application in Medical Image analysis.	√	√			
Chebli, A., et al. (2019)	Semi-Supervised Deep Learning in medical image analysis	√	√	√		
Zhou, T., et al. (2019)	Deep Learning Models in Medical Image Segmentation.	√	√	√		
Jia, X., et al. (2020)	Various Feature Extraction methods are used in polyp detection in WCE image analysis.	√	√	√		
Soffer, S.,et al. (2020).	Survey on Deep Learning models in WCE image analysis	√	√	√		
Rahim, T.,et al. (2020).	Survey on Contemporary CAD in Tumor, Ulcer and Polyp detection in WCE images.	√	√	√		
Muhammad, K., et al. (2020).	Survey on computer vision in WCE Image Analysis	√	√	√		
Trasolini, R., et al. (2021).	AI in WCE image analysis	√	√	√		
This Survey	Deep learning models in WCE image analysis.		√	√	√	√

learning models, performance comparison on various proposed models is insignificant. The significance of labeled dataset and labeling error was described by Ali, H., et al. (2019) and Du, W., et al. (2019) state deep learning as a black box model and question its trustworthiness and model interpretability. Hence this survey suggests surveying DL models in WCE image analysis in terms of Dataset, Domain Knowledge inclusion with the possibility of using Semi-supervised Deep learning in WCE image analysis. To make this deep survey, it considers all the recently published DL-based research literature in WCE image analysis.

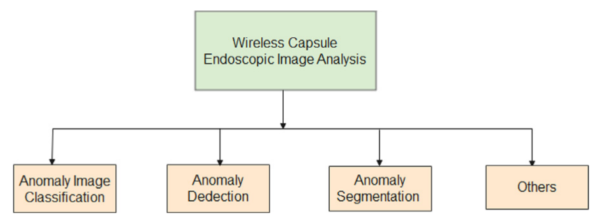

Fig. 2. Research Article Classifications in Wireless Capsule Endoscopy Image

3. Research method

This study focuses on conducting a systematic literature review on wireless capsule endoscopy image analysis that uses Deep Learning Models thus by formulating various research questions. For the past two decades, many reviews were conducted on WCE image analysis considers handcrafted feature engineering methods (Liedlgruber, M., et al. 2011; Litjens, G., et al. 2017). Hence, this survey tune to focus on the recent five years (2015-2021) published deep learning-based articles in the domain of WCE, endoscopy and colonoscopy image analysis. The intended study paves the way to formulate the problem statements by answering the following questions.

Q1: Whether the datasets used in existing deep learning literature are sufficient to train or learn features using supervised deep models?

Motivation: The purpose is to get an idea about the significance of dataset size, class balance and labeled dataset.

Q2: What are the alternative methods available for training with a limited amount of labeled data?

Motivation: To develop a broader knowledge about the existing supervised learning system and suggests a new method either with semi-supervised learning or unsupervised learning that uses unlabelled data for training.

Q3: How to incorporate the domain knowledge into deep learning models to improve model performance?

Motivation: To achieve higher performance, the significance of the domain or expert knowledge should be incorporated into the deep models.

Q4: Whether Transfer learning or Learning from scratch can be applied?

Motivation: Determine whether to construct a new model or to use existing models for transfer learning.

Q5: Instead of generic learning using deep models, can we make a model to learn what we wish for?

Motivation: To develop task-oriented feature learning instead of traditional generic feature learning.

Q6: How to develop self explainable Deep Models to improve the model trustworthiness?

Motivation: To develop a transparent and interpretable model to understand the underlying basics of the model decision-making process to fine-tune the model for improved performance.

4. Deep Learning Methods in WCE

Deep learning algorithms in WCE image analysis are a promising research area to overcome the pitfalls presented in the hand-crafted feature selection method. This survey considers deep learning models proposed for WCE, endoscopy, and colonoscopy image analysis. These proposed works are categorized into Anomaly Image Classification, Anomaly Detection, Anomaly Segmentation and Others as shown in Fig. 2.

4.1. Anomaly image classification

In WCE anomaly image classification, instead of locating the anomaly regions in the WCE images, the deep model classifies whether the given image is normal or abnormal based on the features learned. The performance of the classification model depends on features used to represent anomaly images, the type of input image used and regions of the image used for model training. Most of the existing model uses low-level CNN features to represent anomalies and some of the models use a combination of both the handcrafted features and CNN features for representing anomaly images efficiently. The entire labeled WCE image or labeled batches of images (Region of Interest) is used to learn global feature and local features respectively.

In a classification model, to represent the anomaly pattern, many handcrafted features such as color, texture, statistical features and geometric features are used in the domain of WCE image analysis. The efficiency of the system depends on features used to represent the anomaly patterns. To learn generic features for anomaly pattern representation and classification, the more general deep learning architecture combines convolutional, pooling and fully connected layers as shown in Fig. 3. Deep learning-based generic feature learning provides the best alternative for handcrafted feature engineering methods, it learns low-level generic features by performing convolutional operations.

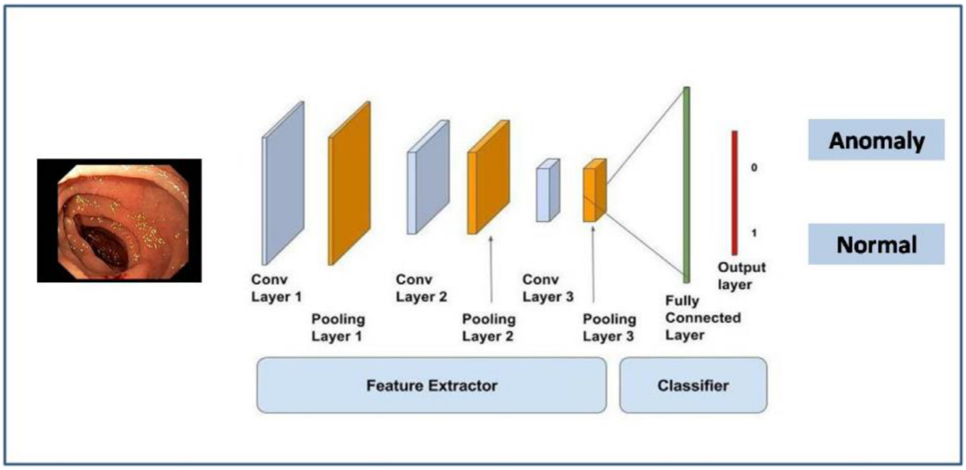

Fig. 3. General Anomaly Image Classification Model Using CNN

Yu, J. S., et al. 2015 suggested a dual training approach for WCE image classification; in the first phase of the training the CNN based classifier model is used to extract features and classify WCE images and in the second training stage a separate CNN model with Extreme Classifier is used for feature learning and image classification. These two separate CNNs share their weights with others to improve the learning capability. Jia, X., Member, S., & Meng, M. Q. (2016) proposed a Deep CNN framework for detecting the bleeding frame in WCE images. The proposed Deep CNN comprises 3 Convolutional layers, 3 max-pooling layers and 2 fully connected layers.

Instead of using color and texture features for anomaly representation, Drozdzal, M., et al. (2016) have proposed a Generic features learning method that uses CNN for different motility characterization in the small intestine. Yuan, Y., & Meng, M. Q. H. (2017) proposed an unsupervised deep CNN model using the stacked autoencoder to learn the features and classify the polyp images in WCE images.Sekuboyina, A. K., Devarakonda, S. T., & Seelamantula, C. S. (2017) suggested CNN for abnormality detection in endoscopy images, the endoscopy images are converted into CIE-Lab and YCbCr color spaces. The patches (interest areas) from these endoscopy images were fed to CNN for feature map generation and the final sigmoid function is used to classify abnormality frames.

Quantitative analysis of celiac disease for capsule endoscopy images using a deep convolutional neural network was proposed by Zhou, T., et al. (2017). GoogleNet was used as a classification model, trained by using both celiac normal and normal images.Ahn, J., et al. (2018) proposed feedback-based deep learning models to classify lesions in the real one. An external embedded platform was used to detect duplicate frames and small bowel lesions. Based on the feedback the frame rate and quality of the capsule can be either increased or decreased. The proposed model achieved low latency, high accuracy, and real-time lesion detection.

For capsule image classification, Cao, Y., et al. (2018) proposed Deep Convolutional Neural Network (DCNN) framework for abnormality detection in WCE images. The proposed DCNN framework consists of six Convolutional layers and is followed by three max-pooling layers to generate feature maps. Nadeem, S., et al. (2018) suggested ensemble feature learning mechanism, features from deep CNN model (VGG-16) and handcrafted features fused for anomaly image classification. H., Hussain, A., et al. (2019) proposed a Transfer learning-based CNN model using AlexNet and GoogLeNet for ulcer image classification in WCE images.Sadasivan, V. S., & Seelamantula, C. S. (2019) suggested a CNN-based methodology to classify abnormal images. Labeled patches in WCE images were identified using chromatic components from the CIE Lab space of the image.

Van Der Putten, J., et al. (2019) proposed a Hybrid classification model that combines CNN and Hidden Markov Model (HMM) for Endoscopy Image Classification. After classifying endoscopy images using CNN, temporal information of the adjutant frame is calculated using HMM. This combination of spatial and temporal helps the model to improve the classification accuracy. Ji, X., et al. (2019) proposed a novel computer-aided classification algorithm to classify endoscopy images. The algorithm uses Color histogram, wavelet transform, and co-occurrence matrix to generate color feature vector and texture feature vector. Also, the model includes BPNN (backpropagation neural network) based novel classification algorithm as a classifier. Park, Y., & Lee, J. (2020) proposed lesion focused knowledge model for class labeling WCE images to detect the GI location and it is corresponding anomalies. It is observed that this research article suggests a knowledge graph to fuse the domain expert knowledge into the deep model for WCE anomaly detection.

4.2. Anomaly detection

Anomaly detection is a process of detecting the presence of anomaly along with region and class as shown in Fig. 4. Object detection in natural images using deep learning architectures uses R-CNN, Fast R-CNN, Faster R-CNN, YOLO and SSD. The performance of these detection networks depends on the Region Proposing Network (RPN) used to identify the Region of Interest (ROI). Direct use of these object detection models in medical image anomaly detection is found to be trivial because the medical images are complex, low resolution and inadequate of an annotated dataset.

Li, P., et al. (2017) proposed a CNN-based hemorrhage detection model based on WCE images. While detecting hemorrhage in WCE images raises a class imbalance issue. To improve those imbalances different data augmentation techniques were used. The author trained the LeNet deep network model from scratch and AlexNet, GoogLeNet and VGG-Net were found adopted for fine-tuning. Aoki, T., Yamada, A., Aoyama, K., & Saito, H. (2018) suggested a DCNN system based on Single Shot Multibox Detector to find erosion and ulceration patches in WCE images. The Experiment was tested on a custom dataset of size 10,400 images out of which 440 images were found as abnormal images.

Zhang, R., et al. (2018) suggested two stages pipelined regression Convolutional neural network for detecting and locating polyp in colonoscopy images. Regression-YOLO object detection algorithm was to extract the spatial features of the polyp regions and temporal information was collected from consecutive frames using an efficient Convolutional operator to refine the region founded by the YOLO object detection algorithm. Shin, Y., et al. (2018) proposed VGG-16 backbone-

Table 2
Deep Learning Models proposed for WCE and Colonoscopy Anomaly Image Classification

Author	Objective	Features Used	Model used	Data set used / size
Ji, X., et al. (2019)	Endoscopy Image Classification	HSV Color Histogram & Texture feature.	Back Propagation neural network.	Custom dataset -1200 Images
Sadasivan, V. S., et al. (2019)	Abnormal Image Classification	CIE color space,	Customized CNN Model.	Custom dataset- 137 Images
Van Der Putten, J., et al. (2019)	Informative frame classification	CNN features	ResNet and Hidden Markov Model.	Custom dataset– 300 Images
Ahn, J., et al. (2018)	Lesion Classification	CNN features	Customized CNN with 3CL and one APL.	-
Cao, Y., et al. (2018)	Anomaly Image Classification	CNN features.	Customized CNN with 5 CL, 5MPL and 2 FCL.	Custom dataset- 5160 Images
Zhou, T., et al. (2017).	Celiac Disease Classification	CNN features	GoogLeNet	Custom dataset– 400 Images
Jia, X., et al. (2016)	Bleeding frame classification	CNN features	Customized CNN with 3 CL, 3 MPL, 2 FCL.	Custom dataset- 10k Images
Drozdzal, M., et al. (2016)	Anomaly Image Classification	Texture feature & CNN features.	Customized CNN model with 3CL, 2 MPL.	Custom dataset– 50 WCE videos
Nadeem, S., et al. (2018)	Anomaly Image Classification	Local and Global texture feature and Generic CNN features.	VGG-16	-
Sekuboyina, A. K., et al.(2017)	Anomaly Image Classification	Local feature / Texture feature from CIE Lab and YCbCr color space.	Customized CNN model with 3 CL, 2 MPL and 2 FL.	Custom dataset- 137 Images
Park, Y., & Lee, J. (2020)	Anomaly Identification	Knowledge Graph	ImageNet	Custom dataset- 36 images
Yu, J. S., et al. 2015	WCE Image Classification	CNN features	Customized CNN model with 8 Layers	Custom dataset- 25 videos
H., Hussain, A., at al. (2019)	Ulcer Image Classification	CNN features	GoogeLeNet and AlexNet	Custom dataset-1875 images
Yuan, Y., & Meng, M. Q. H. (2017)	Polyp image Classification	CNN features	Staked Auto encoder-decoder	Custom dataset – 4000 images

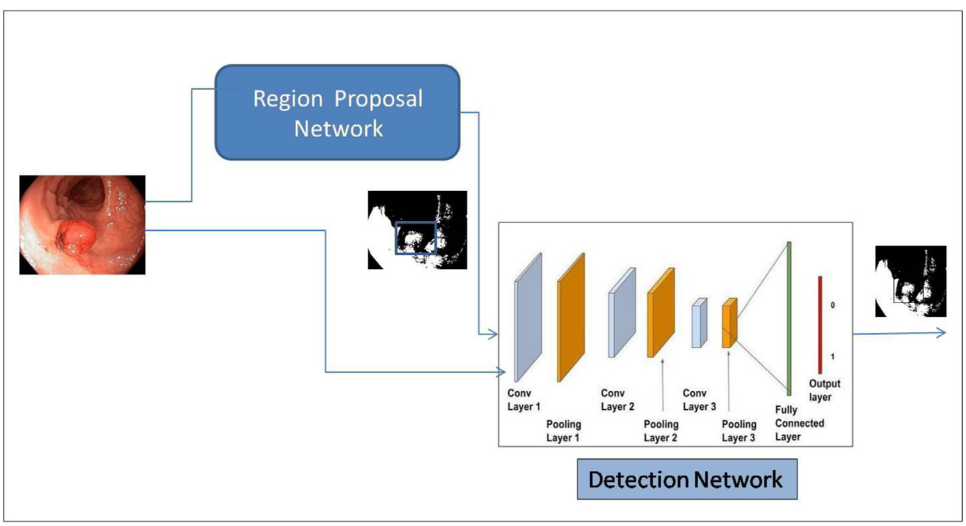

Fig. 4. General Anomaly Detection Network Using Deep Models

based Region Proposing Network (RPN) to identify Region of Interest (ROI) in endoscopy images. Interested regions along with original images fed to the detection network to locate the polyp regions in the given image. Mo, X., Tao, K., Wang, Q., & Wang, G. (2018) proposed Faster-RCNN based deep model for polyp detection in WCE images. The model uses the VGG-16 CNN model as Backbone Region Proposing Network to identify the region of interests and the head network is used to classify the regions detected.

For Hookworm detection, different features must be learned by using different deep learning networks, He, J., et al. (2018) proposed a deep learning-based Deep Hookworm Detection Framework [DHDF] for Hookworm Detection in Wireless Capsule Endoscopy images. The proposed framework concurrently models the visual appearance and tubular pattern of hookworm. To speed up the classification of the proposed framework, it integrates two CNN networks for edge extraction and hookworm classification. Holistically–nested Edge Detection (HED) was adopted to extract edges in WCE images to predict the image using a deep learning model. To detect the tubular regions in WCE images, a Multi-scale dual-matched filter (MDMF) was used. By integration of these two features detects hookworm. Pixel-level deep learning methods increase the computational complexity of the overall abnormality detection system in WCE image analysis. Image level and patch level learning methods were proposed to overcome pixel deep learning methods. For detecting abnormality and localization Koulaouzidis, A., & Plagianakos, V. P. (2018) have proposed a novel method Weakly Convolutional Neural Network (WCNN) to distinguish the normal and abnormal image classification in the WCE video. To reduce the computational complexity Image level labels were used instead of pixel level. To detect the salient point relevant to GI abnormalities in WCE frames, a deep Salient Detection (DSD) algorithm was proposed and the experiment was conducted using both the MICCAI gastro-endoscopy challenge data set and KID dataset

Khan, M. A., et al. (2019) suggested a rank-based feature selection CNN framework for detecting stomach abnormalities in WCE images.

Saliency regions are calculated from WCE images using color features. The WCE image input is fed into DenseNet for computing transfer learning features. These extracted features are used to select the maximum feature value by utilizing kapurs entropy and parallel fusion methods in which Multilayer feed-forward neural network act as a classifier. To detect automatic bleeding in WCE images, Xing, X., et al. (2019) have proposed a hybrid dense network that converts the given input image into polar images by removing the background information. The polar image is then fed into dense network1 to get the saliency map and this is given as input to the dense network2 for classification. The experiment considers the WCE image dataset with 600 normal and 600 abnormal images.

For ulcer detection in WCE images, Wang, S., et al. (2019) proposed Hnet - CNN-based framework that uses ResNet-34 as the base network to learn features for diagnostic purposes. The proposed method was tested on 1416 WCE independent videos with a total of 24,239 frames labeled as ulcer and 24,225 labeled as normal. The performance of the proposed Hnet framework is compared with other Vgg-16, Dense-121 and Inception ResNet-v2. Vallée, R., et al. (2019) recommends Chron disease lesion detection in WCE images using Recurrent Neural Network (RNN). Glimpse network and Detection network were used in the proposed framework. Glimpse network extracts the features from WCE images and the classification is done using a detection network. Two data sets are considered for testing, one with 1800 images of the GIANA competition and the other with 3218 images of the CROHN-IPI (CI) database.

Sharif, M., et al. (2019) proposed a feature fusion approach for anomaly detection in WCE images. Deep CNN features are extracted from VGG-16 and VGG-19 network and geometric features of color-enhanced WCE images are combined to represents anomaly patterns. Lan, L., et al. (2019) proposed CNN based deep cascade network for abnormality detection in the GI tract. Besides, several other methods were adopted; the proposed network model achieves improved performance. To improve the accuracy, the model focus to get the information from the interested region, finding the accurate location of the region, and refining the object boundary it uses the methods Multiregional Combination (MRC), Salient Region Segmentation (SRD), and Dense Region Fusion respectively. To initialize the proposed deep cascade network, transfer learning was used with a pre-trained ImageNet model with more than 7k images of the VOC2007 Classification dataset with a learning rate of 0.01. The model achieves greater classification accuracy than the method proposed with high computation complexity.

Guo, X., & Yuan, Y. (2020) proposed an attention-based semi-supervised deep model for anomaly detection in WCE images. Two CNNs are pipelined to extract the region of interest of the given WCE image using an attention mechanism and extract features from the region of interest to detect the anomaly. This article uses an attention mechanism to identify the region of interest in WCE image analysis. The attention mechanism proposed also identifies the region of interest in the unlabelled data thus makes this architecture is semi-supervised. Nadimi, E. S., et al. (2020) proposed Faster-RPN-based CNN to detect anomalies in WCE images. The Faster-RPN uses both RPN and Fast-RPN to detect the region of interest in the WCE image, along with the original WCE image and the region of interest are fed into the classification network for anomaly detection.

Xiao, Z., & Feng, L. N. (2020) proposed a two-stage target detection network using Improved YOLOv3 architecture for anomaly detection in WCE images. In the first stage feature extraction network is used to extract anomaly features and model the anomaly in WCE and the second stage detection network is used to detect anomalies. Mohammed, A., et al. (2020) proposed an anomaly detection and localization method in the temporal domain within the WCE video frame. Spatial and temporal features are extracted using ResNet-50 and a Residual LSTM block is used to calculate temporal weight between adjacent frames. Finally, a fully Convolutional Neural Network with a sigmoid function is used to locate anomalies in the WCE image. Hajabdollahi, M., et al. (2020) proposed a neural network model based on Bifurcated Convolutional Neural Network to detect multiple abnormalities in different endoscopy images. This research work aims to create a simple neural network for classification and segmentation. Global features for different abnormalities were extracted and fed into the second part where it goes into the different classification frameworks for segmentation and classification.

4.3. Anomaly segmentation

Anomaly segmentation is a process of partitioning the image into multiple segments by grouping similar pixels. The more general architecture of deep learning-based segmentation architecture shown in Fig. 5. that consists of convolutional and max-pooling layers for encoding and deconvolutional and up polling layers for decoding operation.

To segment and detect the angiectasia region in WCE image Pogorelov, K., et al (2018) proposed GAN-based pixel-wise segmenting architectures that use both global and local features for angiectasia representation and random forest for classification. Schurischuster, S., et al (2018) proposed Unet based segmentation architecture to identify the bleeding regions in WCE images. Leenhardt, et al. (2019) proposed a CNN deep feature-based semantic segmentation of anomaly regions in the WCE images. When comparing the conventional hand featured engineering approach, this CNN-based approach seems to be the most promising one. Shvets, A. A., et al. (2019) have proposed DCNN based model for detecting and locate angiodysplasia lesions in WCE images. The author investigated the binary segmentation problem and analyzed different CNN architectures- UNet, TernausNet -11, TernausNet-16 and AlbuNet. The experiment was performed with 600 images of the MICAA 2017 Challenge dataset. Hajabdollahi, M., et al. (2019) suggests a neural network based detection of informative frames by segmenting the bleeding regions in WCE images. The input of WCE images are converted into different color spaces in order to identify the suitable color channel using Mutual Information. The selected color channel is given as input to the MLP (Multi-Layer Perceptron) for quantization of weights to reduce the number of computations. CNN extract features from the GrayScale channel, S channel (HSI) and A channel (CIE Lab) to segment the bleeding region.

Ghosh, T., & Chakareski, J. (2021) have proposed semantic segmentation of bleeding regions in WCE images and this is carried out by cascading the two CNN networks. The first network is used to classify the bleeding image, and the second is used to segment the bleeding regions in WCE images.

4.4. Other applications

For detecting outliers in WCE images, a semi-supervised based deep framework was suggested by Gao, Y., et al. (2016). A standard CNN integrated with long short-term memory was used to find an anomalous graphical pattern between successive image blocks. Outlier Assessment Module was used to distinguish the original and fake outlier by calculating deviations in the given WCE images. Chen, H., et al. (2017) suggested a cascade deep framework for GI content understanding and spatial-temporal features to identify the location of the GI tract.

Iakovidis, Di. K., et al. (2019) Proposed a novel Deep Convolutional Image Registration Model for visual measurement of capsule location in GI tract. Correlation Maps between consecutive frames are calculated via Convolutional operation. Colour features are extracted and fed into a fully connected neural network for 3D measurement of the capsule motion in the GI tract.

A CNN-based model was suggested by Gomes, S., et al. (2019) to find the location of the capsule in the GI tract by finding a homograph between images. The homographs between two consecutive frames were

Table 3
Deep Learning Models proposed for Anomaly Detection in WCE and Endoscopy

Author	Objective	Region Proposal Mechanism	Model used	Data set used / size
Lan, L., et al. (2019)	Abnormality Detection in GI tract	Multi Region Combination (selective search, edge boxes, Objectness)	ImageNet	VOOC2007-7k images
Xing, X., et al. (2019)	Bleeding Detection	Polar Transformation	DenseNet	Custom Dataset – 1.2K images
Wang, S., et al. (2019)	Ulcer Detection	HAnet and Global Average Pooling.	ResNet-34	Custom dataset- 1416 Videos
Khan, M. A., et al. (2019)	Stomach abnormalities Detection	Saliency Map (fusion of HSV and LAB features)	DenseNet	Custom dataset- 12k Images
Vallée, R., et al (2019)	Chron Disease Detection.	Recurrent Attention Neural Network.	VGG-16	GIANA Dataset- 300 Images
Hajabdollahi, M., et al. (2020)	Bleeding Detection	Multi-layer Perceptron	Customized CNN	Custom – 300 Images
Koulaouzidis, A., et al. (2018)	Abnormality Detection and Localization	Deep Feature Map clustering.	Weakly CNN	MICCAI –GI KID – GI
He, J., et al. (2018)	Hookworm Detection	Edge Extraction Network based on VGG	Customized CNN based on InceptionNet	Custom – 440k images
Li, P., et al. (2017)	Haemorrhage Detection	VGG-16	LeNet, AlexNet, VGG-net	Custom dataset- 40k Images
Guo, X., & Yuan, Y. (2020)	Abnormality Classification	Attention Mechanism	DenseNet	CAD-CAP WCE dataset – 2800 images
Nadimi, E. S., et al. (2020)	Polyp Detection and Localization	Faster-RCNN	Faster-RCNN	Custom dataset- 11,300 images
Aoki, T., et al. (2018)	Erosion and Ulceration patches	Single Shot Multibox Detector	Single Shot Multibox Detector	Custom dataset -10,440 images
Shin, Y., et al. (2018)	Polyp Detection.	Faster-RCNN	Inception ResNet	MICCAI 2015 challenge Dataset
Zhang, R., et al. (2018)	Detecting and Locating Polyp.	ResYOLO	ResYOLO	MICCAI 2015 Endoscopic Vision Challenge dataset
Mo, X., et al. (2018)	Polyp Detection	Faster-RCNN	VGG-16	MICCAI2017 endoscopic sub-challenge
Xiao, Z., & Feng, L. N. (2020)	Anomaly Detection	Improved $YOLOV_3$	Darknet-53	Custom dataset- 3120 images
Mohammed, A., et al. (2020)	Anomaly Detection	Residual LSTM	ResNet-50	Custom dataset – 28,300 images
Sharif, M., et al. (2019)	Anomaly Detection	Fusion geometric features and CNN features	VGG-16 & VGG-19	Custom dataset- 4500 images

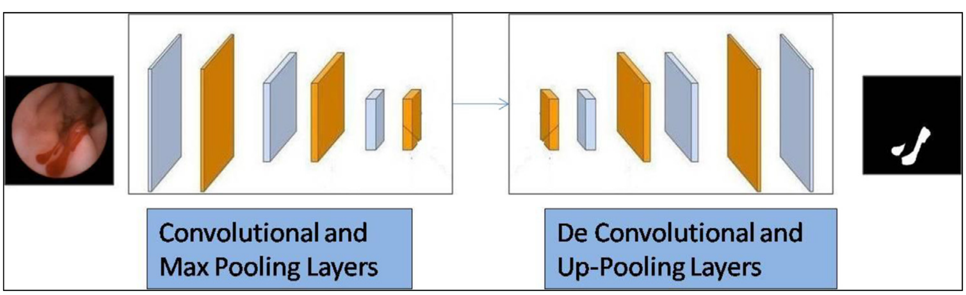

Fig. 5. General Anomaly Segmentation Architecture Using Deep CNN

Table 4
Deep Models proposed for Anomaly Segmentation in WCE Images.

Author	Objective	Model used	Data set used / size
Hajabdollahi, M., et al. (2019)	Bleeding Segmentation	Modified CNN	Custom dataset-350 images
Shvets, A. A., et al. (2019)	Angiodypisia lesion detection	Unet	MICAA 2017 – 600 images
Ghosh, T., & Chakareski, J. (2021).	Bleeding Region Segmentation	SegNet (based on FCNN)	KID dataset- 335 images
Leenhardt, et al. (2019)	Semantic Segmentation of anomaly region.	Customized CNN	Custom dataset – 4166 images
Pogorelov, K., et al (2018)	segmenting angiectasia regions	Semi-supervised –GAN	GIANA 2017 challenge – 600 images
Schurischuster, S., et al (2018)	Segmenting Bleeding Region	Unet	Custom dataset – 430 images

Table 5
Deep Models proposed for other applications in WCE

Author	Objective	Model used	Data set used / size
Gomes, S., et al. (2019)	Homograph Detection	Supervised learning	Custom dataset – 4k Images
Diamantis, D. E., et al. (2019)	Synthetic WCE Image Generation	Semi-Supervised GAN	Custom dataset – 4k Images
Iakovidis, Di. K., et al. (2019)	Visualize the Capsule in GI	Deep Convolutional Image Registration	No Information.
Gao, Y., et al. (2016)	Outlier Detection	Customized CNN	Custom dataset-20k Images
Biniaz, A., Zoroofi, R. A., & Sohrabi, M. R. (2020)	Keyframe Extraction	ResNet-50	KID dataset
Chen, H., et al. (2017)	GI Content Identification	Cascade Deep framework	Custom dataset – 400k images
Sushma, B., et al.(2021)	Video Summarisation	Convolutional Auto Encoder and Decoder	KID dataset

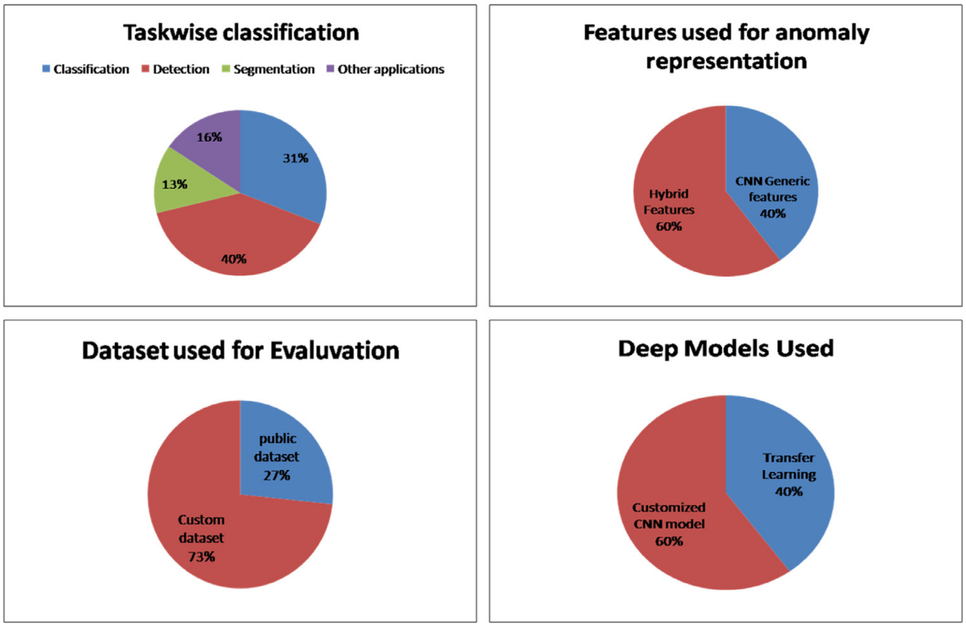

Fig. 6. Quantitative Analysis of Deep Models in WCE image analysis

estimated using the HomographyNet model thus by training the unlabeled data. Diamantis, D. E., et al. (2019) have suggested using artificially generated WCE images to improve the generalization performance of deep learning in inflammatory bowel analysis in Endoscopic images. Generative Adversarial Network was used to synthesize WCE images and Look Back-Fully Convolutional Layer (LB-FCN) was used to classify inflammatory bowel images. Biniaz, A., Zoroofi, R. A., & Sohrabi, M. R. (2020) proposed a keyframe extraction model using the ResNet-50 deep model and color features by eliminating low-quality images. To extract the key feature frames, Sushma, B., & Aparna, P. (2021) have proposed a WCE video summarization method using a deep learning model that measures the similarity between the successive frames in WCE videos by measuring corresponding features.

5. Research findings and scope of opportunities

The analysis of various deep models proposed for WCE anomaly detection and classification exposes the challenges in the quality of the labeled dataset, domain knowledge inclusion and interpretability for model training, making decisions and model understanding respectively. To overcome the challenges, the review was dropped down to explore the possibilities in deep models for developing smart solutions that use unlabelled data, expert knowledge in deep model decision making, and support systems to understand the model behavior. The quantitative summary of various published deep learning research articles is classified and shown in Figure 6 in terms of task-wise classification, features used for anomaly representation, the dataset used for evaluation and deep models used for model training.

5.1. Benchmark dataset and evaluation guidelines

After carefully analyzing the review process, it is observed that neither the benchmark dataset nor the data evaluation metrics were considered for performance analysis in many of the proposals, so, it is difficult to compare the deep models proposed for WCE image analysis using an accuracy determination perspective. Soffer, S., et al. 2020 have pointed out some benchmark datasets and evaluation guidelines for WCE image analysis in the Medical image challenging contexts like MICCAI, GIANNA and Kaggle.

5.2. Semi-supervised deep models

In the domain of Wireless Capsule Endoscopy image analysis, manual annotation of images using experts is a time-consuming and expensive process that raises issues in obtaining labeled datasets. Also, it opens a new research direction in semi-supervised and unsupervised deep learning models in WCE image analysis. Already very few semi-supervised deep learning methods such as co-training, self-labeling, ensemble methods, consistency-based methods and generative methods were proposed for medical image analysis. These methods use both labeled and unlabelled datasets for training (Chebli, A., et al. 2019) and the same can be applied to WCE image analysis. Weekly supervised deep learning is the best alternative approach for supervised learning that uses image-level annotation instead of pixel-level annotation images to reduce the annotation cost.

5.3. Attention guided feature learning

The attention-guided deep learning model improves the performance of the traditional CNN in computer vision applications using content-based interactions (Schlemper, J., et al. 2019). To overcome the computational complexity associated with cascaded deep learning models in object detection networks; this attention mechanism is used to identify the regions essential for target prediction. So many attention-based models like spatial attention, channel attention and standalone attention models were proposed to identify the discriminative features (Guo, X., & Yuan, Y. 2020).

5.4. Expert knowledge inclusion in model decision making

Making a deep learning model and making it think like a radiologist is a challenging task. The radiologist has a lot of experience in detecting anomalies and human anatomy (Xie, X., et al. 2020). Knowledge of the radiologist can be incorporated into deep learning models in identifying the features and the area in which the radiologist is interested in. This expert knowledge can be encoded in such a way that, it can be fed into a deep model for training. For example, handcrafted features such as color, texture and geometric features can also be used along with CNN generic features for anomaly detection. Another solution is obtained by constructing a knowledge graph with human anatomy information, features and different anomalies using Graph Neural Network (GNN). These

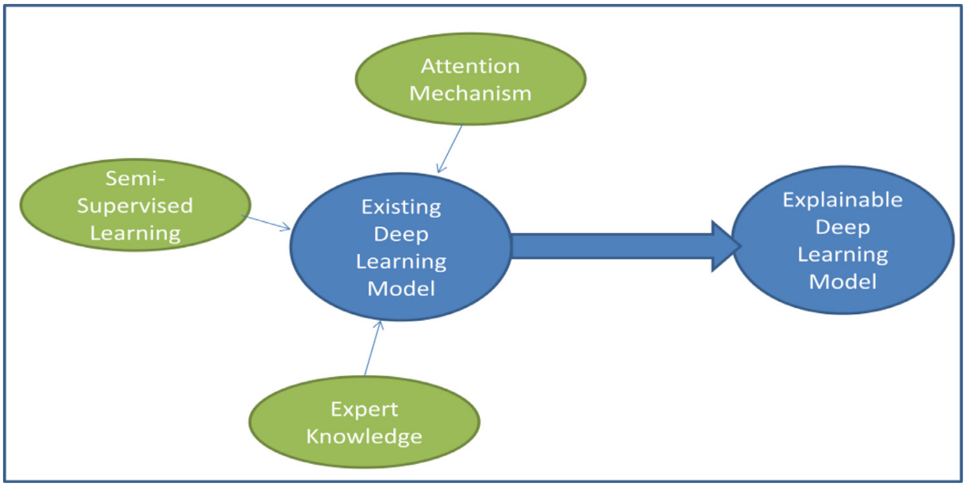

Fig. 7. Role of Attention mechanism and Expert knowledge in developing Explainable Deep learning model

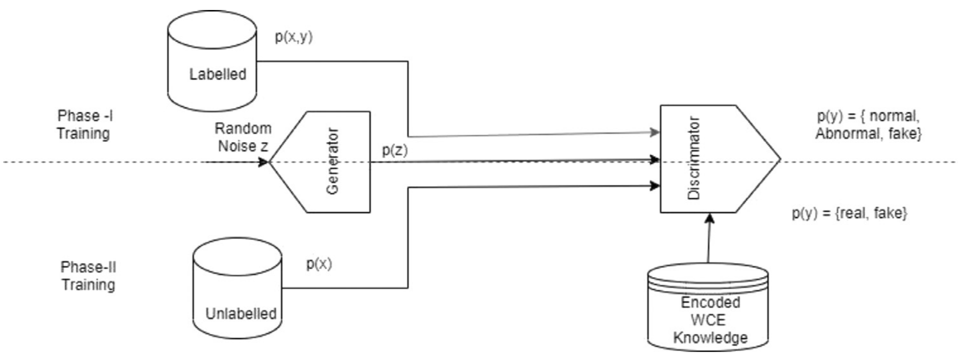

Fig. 8. GAN-based Semi-supervised model for WCE image classification.

encoded knowledge features are used along with the standard CNN features for anomaly detection (Zhang, X., et al. 2018).

5.5. Trustworthiness of the model

Explainable AI is another promising research area of artificial intelligence. The model explainability helps to understand the model in a better way and helps to improve the model performance. The difficulty level of the model explainability varies from basic machine algorithms to complex deep learning model architecture (Angelov, P., & Soares, E. 2020). Deep learning models with reasoning capabilities improve the explainability of the model with the help of attention-guided learning and expert knowledge inclusion in the model decision-making process. A lot of research initiatives like textual justification, concept vector and expert knowledge were already taken to develop an explainable AI model in the field of Computer Vision (Trasolini, R., & Byrne, M. F. 2021).

6. Proposed semi-supervised deep model using generative adversarial network

In the proposed Domain Adopted Generative Adversarial Network (DA-GAN) model for WCE image classification, the survey considers both labeled and unlabelled images for model training. The training process is carried out in two different phases, one with a labeled dataset and the other with the unlabelled dataset. Encoded domain knowledge vectors are used as auxiliary components in making decisions. An optimized loss function is used to update model weights that include both supervised loss and unsupervised loss. The overall architecture of the proposed system is depicted in Fig. 8 and the loss function used to optimize the network weights is present in Eqs. 1, 2 and 3. The proposed model is tested using Kvasir-Capsule, a video capsule endoscopy dataset by excluding the implementation of the Domain Knowledge inclusion module. In the earlier results shows that the overall classification accuracy of the proposed semi-supervised DA-GAN model slightly improved compared to other supervised deep models thus by learning the unlabelled data.

$$L_{overall} = L_{sup} + L_{unsup}$$

$$l = -E_{x,y\sim p_d}(x, y)\left[\log p_{model}(yx)\right] - E_{x\sim p_g}\left[\log p_{model}(y = k + 1x)\right]. \tag{1}$$

$$l_{sup} = -E_{x,y\sim p_d}(x, y)\left[\log p_{model}(yx)\right]. \tag{2}$$

$$l_{unsup} = -\left\{E_{x\sim p_d}(x)\log\left[1 - p_{model}(y = k + 1x)\right] - E_{x\sim p_g}\left[\log p_{model}(y = k + 1x)\right]\right\}. \tag{3}$$

7. Conclusion

The review of deep models used for detecting abnormality in WCE images was explored. The significance of using deep models for WCE image analysis also explores the dataset considered, merits and pitfalls. It is observed that existing deep models are supervised learning and use a limited amount of labeled data for training. Due to the class imbalance, the quality of the training data is found to be poor. The proposed semi-supervised deep learning model resolves the insufficient labeled dataset issue by using unlabelled data for model training and thus improves the overall classification accuracy by comparing other supervised models. In the future, domain knowledge can be incorporated into proposed semi-supervised deep models for improving model decision-making and an attention mechanism can also be used to learn target-specific learning. Further, developing a decision tree support model helps to understand the model behavior and improves the interpretability of the model.

Declaration of competing interests

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

References

Ahn, J., Loc, H. N., Balan, R. K., Lee, Y., & Ko, J. (2018). Finding Small-Bowel Lesions : Challenges in. *Computer, 51*, 68–76. 10.1109/MC.2018.2381116.

Ali, H., Sharif, M., Yasmin, M., Rehmani, M. H., & Riaz, F. (2019). A survey of feature extraction and fusion of deep learning for detection of abnormalities in video endoscopy of gastrointestinal-tract. *Artificial Intelligence Review*. 10.1007/s10462-019-09743-2.

Aoki, T., Yamada, A., Aoyama, K., & Saito, H. (2018). Automatic detection of erosions and ulcerations in wireless capsule endoscopy images based on a deep convolutional neural network. *Gastrointestinal Endoscopy*. 10.1016/j.gie.2018.10.027.

Cao, Y., Yang, W., Chen, K., Ren, Y., & Liao, Q. (2018). Capsule endoscopy image classification with deep convolutional neural networks. In *2018 IEEE 4th International Conference on Computer and Communications* (pp. 1584–1588). ICCC. 2018. 10.1109/CompComm.2018.8780859.

Chebli, A., Djebbar, A., & Marouani, H. F. (2019). Semi-Supervised Learning for Medical Application: A Survey. In *Proceedings of the 2018 International Conference on Applied Smart Systems* (pp. 1–9). ICASS. 2018, November. 10.1109/ICASS.2018.8651980.

Ciuti, G., Menciassi, A., & Dario, P. (2011). Capsule Endoscopy : From Current Achievements to Open Challenges. *IEEE Reviews in Biomedical Engineering, 4*, 59–72. 10.1109/RBME.2011.2171182.

Du, W., Rao, N., Liu, D., Jiang, H., Luo, C., Li, Z., Gan, T., & Zeng, B. (2019). Review on the Applications of Deep Learning in the Analysis of Gastrointestinal Endoscopy Images. IEEE Access, 7, 142053–142069. https://doi.org/10.1109/ACCESS.2019.2944676

Fu, Y., Zhang, W., Mandal, M., & Meng, M. Q. H (2014). Computer-aided bleeding detection in WCE video. *IEEE Journal of Biomedical and Health Informatics, 18*(2), 636–642. 10.1109/JBHI.2013.2257819.

He, J., Wu, X., Jiang, Y., & Peng, Q. (2018). Hookworm Detection in Wireless Capsule Endoscopy Images With Deep Learning. *IEEE Transactions on Image Processing, 27*(5), 2379–2392. 10.1109/TIP.2018.2801119.

Ji, X., Xu, T., Li, W., & Liang, L. (2019). Study on the classification of capsule endoscopy images. *Eurasip Journal on Image and Video Processing*, (1) 2019. 10.1186/s13640-019-0461-4.

Khan, M. A., Sharif, M., Akram, T., Yasmin, M., & Nayak, R. S. (2019). Stomach Deformities Recognition Using Rank-Based Deep Features Selection. *Journal of Medical Systems, 43*(12). 10.1007/s10916-019-1466-3.

Koulaouzidis, A., & Plagianakos, V. P. (2018). Detecting and Locating Gastrointestinal Anomalies Using Deep Learning and Iterative Cluster Unification. *IEEE Transactions on Medical Imaging, 37*(10), 2196–2210. 10.1109/TMI.2018.2837002.

Leenhardt, R., Vasseur, P., Li, C., Saurin, J. C., Rahmi, G., Cholet, F., Becq, A., Marteau, P., Histace, A., Dray, X., Sacher-Huvelin, S., Mesli, F., Leandri, C., Nion-Larmurier, I., Lecleire, S., Gerard, R., Duburque, C., Vanbiervliet, G., Amiot, X., & Romain, O. (2019). A neural network algorithm for detection of GI angiectasia during small-bowel capsule endoscopy. *Gastrointestinal Endoscopy, 89*(1), 189–194. 10.1016/j.gie.2018.06.036.

Liedlgruber, M., & Uhl, A. (2011). Computer-aided decision support systems for endoscopy in the gastrointestinal tract: A review. *IEEE Reviews in Biomedical Engineering, 4*, 73–88. 10.1109/RBME.2011.2175445.

Mo, X., Tao, K., Wang, Q., & Wang, G. (2018). An efficient approach for polyps detection in endoscopic videos based on faster R-CNN. In *8 24th International Conference on Pattern Recognition (ICPR)* (pp. 3929–3934).

Nadeem, S., Tahir, M. A., Naqvi, S. S. A., & Zaid, M (2018). Ensemble of texture and deep learning features for finding abnormalities in the gastro-intestinal tract. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 11056 LNAI*. Springer International Publishing. 10.1007/978-3-319-98446-9_44.

Pogorelov, K., Ostroukhova, O., Jeppsson, M., Espeland, H., Griwodz, C., De Lange, T., Johansen, D., Riegler, M., & Halvorsen, P. (2018). Deep Learning and Handcrafted Feature Based Approaches for Automatic Detection of Angiectasia. In *Proceedings - IEEE Symposium on Computer-Based Medical Systems* (pp. 381–386). 2018-June(March). 10.1109/CBMS.2018.00073.

Sadasivan, V. S., & Seelamantula, C. S. (2019). High accuracy patch-level classification of wireless capsule endoscopy images using a convolutional neural network. In *Proceedings - International Symposium on Biomedical Imaging* (pp. 96–99). 2019-April(Isbi). 10.1109/ISBI.2019.8759324.

Sainju, S., Bui, F. M., & Wahid, K. A. (2014). Automated bleeding detection in capsule endoscopy videos using statistical features and region growing. *Journal of Medical Systems, 38*(4). 10.1007/s10916-014-0025-1.

Schurischuster, S., Remeseiro, B., Radeva, P., & Kampel, M. (2018). A Deep Learning Approach for Red Endoscopies. *AG Springer Nature, 1*(June), 553–561. 10.1007/978-3-319-93000-8.

Shin, Y., Qadir, H. A., Aabakken, L., Bergsland, J., & Balasingham, I. (2018). Automatic colon polyp detection using region based deep CNN and post learning approaches. *IEEE Access, 6*, 40950–40962. 10.1109/ACCESS.2018.2856402.

Van Der Putten, J., De Groof, J., Van Der Sommen, F., Struyvenberg, M., Zinger, S., Curvers, W., Schoon, E., Bergman, J., & De With, P. H. N (2019). Informative Frame Classification of Endoscopic Videos Using Convolutional Neural Networks and Hidden Markov Models. In *Proceedings - International Conference on Image Processing, ICIP, 2019-Septe* (pp. 380–384). 10.1109/ICIP.2019.8802947.

Xing, X., Yuan, Y., Jia, X., & Meng, M. Q. (2019). A SALIENCY AWARE HYBRID DENSE NETWORK FOR BLEEDING DETECTION IN WIRELESS CAPSULE ENDOSCOPY IMAGES. In *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)* (pp. 104–107).

Zhang, R., Zheng, Y., Poon, C. C. Y., Shen, D., & Lau, J. Y. W (2018). Polyp detection during colonoscopy using a regression-based convolutional neural network with a tracker. *Pattern Recognition, 83*, 209–219. 10.1016/j.patcog.2018.05.026.