Wireless capsule endoscopy devices for imaging and cancer detection in digestive gland using AI

Dr. Shelej Khera , Parulpreet Singh

School of electronics & electrical engineering
Lovely Professional University,Punjab,India
shelej.22390@lpu.co.in

Abstract: Currently Cancer detection and imaging examination in gastrointestinal (GI) tract depends on manual viewing and reading by doctors. This method need expert doctors who possess high level of skills and experience in clinic. The central objective of this review paper is to present various features of commercially available wireless endoscopy capsules and to introduce various research methods and algorithms for detecting cancer in digestive system using Machine learning and Deep Learning.

Key words : CMOS, ASIC, RF,USB

Introduction: The cases of cancer affecting the people in world is growing due to various reasons like increasing age, change in dietary, exhausting lifestyle and many more. According to cancer statistics report in 2020 there will be around 1.8 million new cases of cancer will be detected and around 0.6 million people estimated to die because of cancer in USA [1]. Cancer will beat cardiovascular disease in causing death to people in coming few years in USA [1]. Malignant cancers are the dominant reason for ending human life and making cancer a global health challenge. Digestive tract and glands are mainly affected by malignant cancer. Esophageal cancer, colorectal cancer, gastric cancer, pancreatic cancer and liver cancer are main types of cancer in digestive system [2]. Right now, cancer related deaths in the world are mostly because of gastrointestinal cancers [3].

Detection and treatment of cancer at early stage increases the survival rate in patients. Hence there is the need of accurate detection system for cancer. The most common and used is medical image diagnosis using wired endoscopy for detection of cancer. Wired endoscopy devices are used to find defects and deformities in gastrointestinal tract [4, 5]. The method no matter is effective and traditional but it causes distress and produce complexity in cancer detection as lengthy and elastic tube is pushed in gastrointestinal tract [6]. In this process it is very tough to observe the largest region of small intestine [7]. Images obtained are mainly depends on doctors for examination and efficient detection. For these purpose doctors experience, skills, time and attentiveness are prime. With the increased in the amount of imaging data have put more challenges on radiologists. With the advancement in artificial intelligence provides an opportunity to study bio medical images and achieve error less detection of cancer. This review paper summarise the various methods implemented by many authors in automatic cancer detection. This paper review the functionality of commercially available endoscopic capsule.

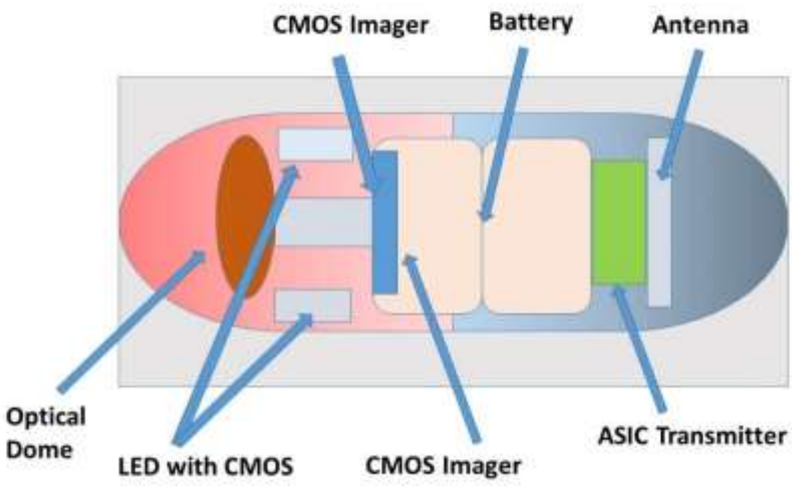

Figure 1 Structure of Wireless Endoscopic Capsule

Table 1. Important Features of Wireless capsule Endoscopy Devices

Wireless Capsule Endoscopy Devices	Company	Target	Size (mm)	Mass (gm)	Image Sensor Technology	Resolution Rows x Columns	Transciever	RT
PillCam SB	Medtronics	SMALL BOWEL	26 x 11	4	1 CMOS	256 x 256	RF	YES
PillCam SB2		SMALL BOWEL	26 x 11	2.9	1 CMOS	256 x 256	RF	YES
PillCam SB3		SMALL BOWEL	26 x 11	3	1 CMOS	256 x 256	RF	YES
PillCam ESO		ESOPHAGUS	26 x 11	2.9	2 CMOS	256 x 256	RF	YES
PillCam ESO2		ESOPHAGUS	26 x 11	2.9	2 CMOS	256 x 256	RF	YES
PillCam Colon		COLON	31 x 11	2.9	2 CMOS	256 x 256	RF	YES
PillCam Colon2		COLON	31 x 11	2.961	2 CMOS	256 x 256	RF	YES
Miro Cam	Intromedic	SMALL BOWEL	24.5 x 10.8	3.25	1 CMOS	320 x 320	HBC	YES
Endo Capsule	Olympus	SMALL BOWEL	26 x 11	3.3	1 CCD	1920 x 1080	RF	YES
OMOM	JinShan	SMALL BOWEL	27.9 x 13	6	1 CMOS	640 x 480	RF	YES
Capso Cam	Capso Vision	SMALL BOWEL	31 x 11	4	4 CMOS	1920 x 1080	USB	NO

A typical structure of wireless endoscopic capsule is shown in Fig.1. This electronic WCE capsule consists of optical dome, CMOS Image, battery and antenna. The important features of commercially available wireless capsule endoscopy devices are summarized in Table 1.

Now after comparing the features of wireless endoscopic capsules, this paper analyses the algorithms and methods used in cancer detection. This paper discuss and compares the methods used in detecting esophageal, colorectal, liver and pancreatic cancer.

Esophageal Cancer Detection

It is common cancer in the digestive system. It faces the problem of early and poor detection and have affected 0.5 million people every year. This cancer is ranked sixth in cancer causing deaths estimated to have 0.4 deaths every year [8]. When esophageal cancer is detected and cured at advanced stage it need intrusive cure and the prognosis is very less. Hence, early recognition is vital in cancer treatment.

The data of 384 patients affected by esophageal cancer was collected and 8 thousands images have been analysed using AI capable diagnosis system by Horie et al. [9]. In these proposed method AI diagnostic system was founded by deep learning which showed high sensitivity for detecting esophageal cancer. The method CNN was trained by outsized number of endoscopic images. The model prepared 8428 esophageal affected images which were already tested by adenocarcinoma as training sets of images. The proposed model have taken 27 seconds to process 1118 images and to find the cancer in the given data. The sensitivity was about 98% in this model. The CNN model was successful in detecting all seven cancer lesions with size as small as 10 mm [9].Yousefi et al. [10] proposed a 3D CNN model called as DenseUnet for detection esophageal cancer. The model has used the idea of dense blocks with down sampler and up sampler. The network helps in finding out the relevant deep features. The model was tested on 553 chest images of 49 patients and it has achieved the dice similarity coefficient value 0f 0.73 and mean surface distance of 95%. The proposed network has obtained challenging results [10].Yu Z. et al. [27] proposed a model with supervised machine learning embedded with analysis of texture for biomedical image processing. The method used divisible grayscale uneven texture present in image features to shrink the complexity of machine learning. This has enable high processed speed per second.

Colorectal Cancer Detection

Zhang et al. [14] used regression based CNN using pipeline to detect the polyp during colonoscopy. The model was constructed in two phase first it learns spatial coordinates features and was trained by non-medical image data and then it's tuned for colonoscopy image data set. The model detects polyps with precision of 88.6% with a speed of 6.5 frames per second [14]. Ren et al. [15] proposed CAD model that extracts the three features geometrical, morphological and textual. The model was applied to 153 patients. Mohammed et al. [16] proposed deep encoder decoder to address problem of colonoscopy. The method works on encoder network that uses pre trained weights. In the initial encoder it uses pre trained weights and initializes random in latter stages. Both the encoder are concatenated by sum skip operation to efficiently optimize large variation of testing data. The results obtained by the method on ASU-mayo clinic database are better in performance [16].

Liver Cancer Detection

Liver cancer is affected because of tumors in liver. The appearance of tumors are not same and there visual look after injection of the contrast medium. The detection of tumors in liver is tough job. Ben-cohen et al. [17] proposed the liver lesion detection models framework. Which is made up of two modules. The first module is fully convolutional neural network which inputs axial slices to find the lesions. The target slice at the centre and two to adjacent above and below. The model predicts the lesions probability. Y. Todoroki et al. [18] proposed tumor detection in liver in two steps. First step the segmentation algorithm is applied to segment liver from the CT images. The second steps gives the probability of the pixel belonging to tumor by deep convolutional neural network (DCNN) [18].

The proposed layers of convolutional in DCNN are proposed to find out useful features. The pooling layers reduces the spatial coordinate's variations. Full connected layer is used for classification of tumor and to find tumor probability [18].Ben-cohen et al. [19] proposed a system on fully convolutional network (FCN). It includes to synthesize images obtained from CT and to find malignant lesions. The synthesized images are used for automatic detection of lesions [17]. In the advancement to previous work Ben-cohen et al. [19] avoids the blending of images which saves time and manually defining the threshold which ultimately improves the system performance. The method have used deep learning techniques for convolutional networks and conditional adversarial network [19].

Hoogi A. et al. [20] proposed liver lesions and nodes detection in three steps. First it uses 3D Haar transformation using available image of the organ region interest. Next it uses Adaboost classifier for feature selection and classification. The features reduction is done in this step only. Third step is to train another classifier prone to the candidates [20].

Pancreatic Cancer Detection

Pancreatic ductal adenocarcinoma, responsible for almost all malignant pancreatic cancer has very high death causing rate. Various research has been made in this field, but detection of cancer at last and non-curable stage causing high mortality [21]. Siqi li et al. [22] proposed model where segmentation of images will be performed by simple linear iterative clustering on images obtained by CT. The model applies dual threshold principal component analysis to extract the most important and information based components. The model was tested on 80 cases and had achieved the accuracy of 94.7% right identification [21].

Boroujeni A etal. [23] Proposed a model used K-means clustering for segmentation of captured images into region of interest. The process was done before extracting the features. The neural network with multilayer perceptron was trained to find and distinguish the benign from malignant tumor cases. The result obtained from the model were accurate to 77% for benign and malignant tumor categories. Li H et al. [24] has given a model with Dense-Net for feature extraction and classification. It contains three convolutional blocks. Two max pooling blocks between each, the kernel of size 3x3 is used with zero padding. The proposed method achieved the accuracy of around 73% [24].

Table 2. Overview of papers detecting various cancer using different approach

Sr. No.	Cancer Detection Type	Reference	Applied Algorithm	Images Data	Approach/ Application
1.	Esophageal Cancer Detection	Yu Z et al. [27]	AdaBoost Classification	Endoscopy	Text Features, Histogram manipulation and detection of esophageal adenocarcinoma using AdaBoost Classifier
		Riel S . [26]	CNN	Endoscopy	Esophageal detection using random forest, support vector machine and CNN
		Ebigbo et al. [28]	CNN	Endoscopy	Residual net architecture with CNN for detecting early esophageal adenocarcinoma
		Horie I. [10]	CNN	Endoscopy	White light and narrow band imaging with CNN to detect esophageal cancer
2.	Colorectal	Mohammed et al.[16]	CNN	Colonoscopy	Colon polyp detection using encoder decoder CNN
		Ren et al.[15]	Random forest Algorithm	CT Images	Morphological operation and features to colon tumor
		Zhang et al.[14]	CNN	Colonoscopy	Colon polyps detection using CNN with regression
3	Liver Cancer Detection	Todoroki et al.[18]	CNN	CT	Liver cancer detection using CNN
		Cohen et al.[17]	FCN	CT	Sparsity based dictionary learning with FCN for liver lesion detection
		Cohen I.[19]	FCN and GAN	CT/PET	Generative adversarial network (GAN) used with FCN for automatic detection of liver cancer detection
		Hoogi et al.[20]	CNN	CT	CNN with space learning and contour modelling for automatic liver cancer detection
4	Pancreatic Cancer Detection	Li .[22]	SVM	CT	SVM with random forest to detect cancer
		Boroujeni et al.[23]	ANN	Pathological Slices	Perceptron neural network with multi-layer to detect cancer
		Li .[24]	CNN	CT	Dense CNN to detect pancreatic cancer
		Zhang . [25]	SVM	EUS	Text Feature and Support Vector Machine for cancer detection

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