JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Automated Stomach Cancer Detection System Using Multi-Layer CNN and Random Forest

S.Sunitha M.Sc [1*], Dr.S.S. SUJATHA [2]

[1] Research Scholar, South Travancore Hindu College, Nagercoil, Manonmaniam Sundaranar University, Tirunelveli, 627 012

2 Associate Professor, Computer Science and Applications, South Travancore Hindu College, Nagercoil, 629 002.
[1]sunithaajistenin@gmail.com, [2]sujaajai@mail.com.

Abstract: Among the recognized types of malignant tumors, one that cannot be detected early and presents no symptoms is intestinal cancer. Wireless capsule endoscopy is a clinical investigation for detecting stomach cancer and other stomach related ailments. Due to the stomach's structure and color, detecting stomach cancer in its early stages with WCE images is a challenging and time-demanding medical procedure. This research aims to automate the process detection of malignancy in WCE images with high accuracy. Convolutional Neural Networks and Machine Learning techniques are used in this study to detect stomach cancer early. Automatic feature extraction from WCE images is performed using a Multi-Layer CNN (ML-CNN) feature extractor. Additional color and texture features are extracted from WCE images using Correlated Feature Extraction (CFE). The features retrieved using the Multi-Layer CNN (ML-CNN) technique are classified using RF into two categories. MAE and RMSE are used to demonstrate the efficacy of the suggested strategy based on training and detection of stomach cancer. The classification accuracy of the proposed Multi-Layer CNN (ML-CNN) technique is 95%, which is superior to other existing approaches.

***IndexTerms* -. Wireless Capsule Endoscopy, Image Segmentation, Image Pre-Processing, CNN, Polyp Detection, Deep Learning.**

I. INTRODUCTION

Bowel cancer is not a short-term disease; it is a slow-growing chronic disease [7]. Polyp is the initial stage of bowel cancer. It comes in various sizes and resembles the human digestive tract in structure and color. Slightly larger polyps increase the likelihood of developing malignant cancer. Additionally, intestinal bleeding is a symptom of colon cancer [8][9]. Bowel cancer is primarily caused by ageing, which is difficult to forecast. .

The terrible problem is that it is impervious to early diagnosis. A specialized diagnostic procedure termed WCE is used to discover malformations in a patient's gastrointestinal tract in the medical field. WCE was created in the 1990s by gastroenterologists. In 2001, the FDA approved WCE for medical research [10]. WCE is capable of diagnosing a variety of intestinal illnesses without requiring surgery. WCE is popular with patients and professionals due to its non-invasive nature. WCE is a wireless communication device that is used to undertake a comprehensive examination of the human digestive tract in a therapeutic setting. The WCE is composed of the following components: a camera, batteries, a wireless connection device, and sensors [11] [12]. WCE communicates with a wireless communication device that is located outside the human abdomen. WCE medical examinations do not cause the patient any discomfort or agony. Following the WCE medical examination, the patient can resume his regular routine.

The primary goal of this research is to develop an automated method for more accurate and rapid detection of anomalies in WCE images. In biomedical imaging. Deep learning is critical [13]. This study aims to combine deep learning and machine learning technologies to improve the efficiency of stomach cancer diagnosis. This procedure helps to limit the likelihood of false positives and negatives throughout the stomach cancer detection process. This method of feature extraction improves the training's efficiency and accuracy. Experiments have established this.

Section II of this article discusses the critical methodologies and algorithms for detecting stomach cancer. Section III fully discusses the proposed methodology for detecting stomach cancer. The experimental data and analysis are presented in Section IV. Finally, Section V discusses the recommended work's conclusion.

II. LITERATURE REVIEW

Numerous studies have been conducted on the use of deep learning to diagnose gastric cancer using endoscopic pictures, including classifications of gastric cancer and healthy people and automated recognition of gastric cancer regions.

Shichijo et al. used a convolutional neural network (CNN) to predict Helicobacter pylori infection and attained a sensitivity of 88.9 percent and a specificity of 87.4 percent [1]. Li et al. used magnified narrow-band imaging (NBI) to develop a method for discriminating between gastric cancer and normal tissue [2]. They classified using the Inception-v3 CNN model and attained a

sensitivity of 91.18 percent and a specificity of 90.64 per cent. Zhang et al. used CNN to construct a system for classifying precancerous illnesses (polyp, ulcer, and erosion) and achieved an accuracy of 88.9 percent [3].

Hirasawa et al. devised a single-shot multi-box detector (SSD), an object detection model, to automate the identification of early-stage gastric cancer [4]. Detection sensitivity was 92.2 percent, and positive predictive value was 30.6 percent. Sakai et al. also developed a method for detecting gastric cancer objects using micro patch endoscopic images by distinguishing gastric cancer regions and normal regions [5]. The approach had a detection sensitivity of 80.0 percent and a specificity of 94.8 percent, respectively.

We developed a method for extracting early gastric cancer 's existence and invasive regions utilizing Multi-Layer CNN, capable of object identification and segmentation [6]. We demonstrated that automated identification of early gastric cancer has a sensitivity of 97.0 percent and segmentation concordance of 70%. While the approach was sufficiently sensitive for detection, the average number of false positives (FP) per image was 0.10. (3.0 per patient). The Multi-Layer CNN was utilized to establish an object detection model for common natural photos in this study. It correctly diagnosed lesions with a relatively obvious shape that generated unevenness because it recorded the object's clear outline.

On the other hand, the object detection model missed many early gastric cancer lesions in which just the surface of the stomach mucosa was malignant due to imprecise contours. When used for segmentation rather than object identification, a CNN analyses patterns in the image's local regions and divides the entire image into regions based on whether they match the recovered patterns. This behavior of identifying individual regions while studying details is comparable to that of an expert physician observing the gastric cavity, and segmentation techniques may improve the accuracy of automated lesion diagnosis.

On the other hand, CNNs' segmentation output frequently contains a large number of tiny regions. Using the FP reduction strategy to exclude these may significantly reduce the amount of FPs and enhance detection performance. As a result, segmentation algorithms that eliminate small excess regions are practical for automating the detection of gastric cancer and determining the invasion's extent.

III. Proposed Method

Fig.1 illustrates the overall graphical representation of the proposed automated stomach cancer detection system..

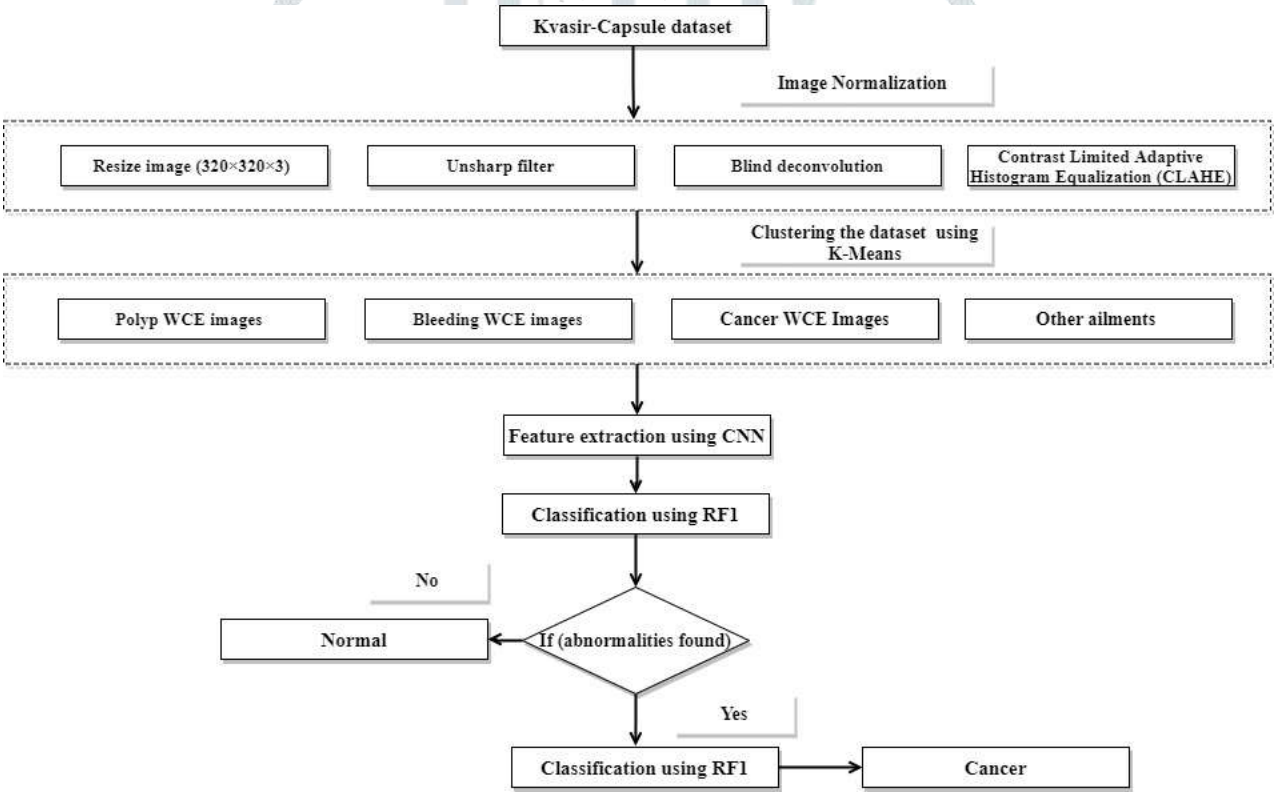


Figure1 Overall architecture of the proposed Automated Bleeding Image Detection

A. Dataset details

The Kvasir dataset contains pictures that have been annotated and confirmed by medical doctors (seasoned endoscopists), and includes various classes that depict anatomical landmarks, pathological findings, or endoscopic procedures in the gastrointestinal tract, i.e., hundreds of images for each class. The quantity of images is sufficient for various tasks, including image retrieval, machine learning, deep learning, and transfer learning, among others. For example, the Z-line, pylorus, and cecum are anatomical features, while esophagitis, polyps, and ulcerative colitis are pathological findings. The dataset consists of photos ranging in resolution from 720x576 to 1920x1072 pixels that have been arranged into distinct folders titled according to their content. Several of the included image classes include a green picture that illustrates the endoscope's position and configuration inside the bowel via the use of an electromagnetic imaging system that may aid in image interpretation. Color Feature Extraction.

Figure 2: Different medical investigation images of Kvasir-Capsule dataset

B. Image normalization

Normalization of medical images are crucial for disease diagnosis and classification. Medical images are highly noisy, tone mapping, and dynamic. WCE is typically available in a number of different configurations. As a result, the images generated by WCE differ in terms of quality and size. To obtain a more precise classification result, it is required to include some significant preprocessing methods for wireless endoscopic images. When the WCE settings are modified, the size and quality of the WCE images are also changed. When the WCE images are large, creating a model involves considerable time and computer hardware requirements. In this proposed research, the image is downsized to 320×320×3 pixels before to training and testing. Human interior organs are often quite dark as a result of a lack of light penetration. As a result, the photos generated by WCE are likely to be rather dark. When this photograph is processed in its raw state, it generates an image with poor accuracy. Hence, a novel contrast enhancement technique must be developed to produce a highly accurate WCE cancer detection system. The suggested method utilizes an unsharp filter, blind deconvolution, and Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance WCE images. The unsharp mask filter and blind deconvolution repair blurred WCE images. CLAHE is a contrast-balancing technique for recovering and balancing photographs.

C. CNN feature extraction

In this suggested study, CNN is employed to extract the essential factors that influence the stomach cancer of WCE images. The proposed stomach cancer detection system's overall architecture is depicted in figure 3. Primarily, the input texture features from the WCE images database are gathered. The WCE cancer images consist of texture variation, shown in figure 2. The intermediate texture features and the essential variations of input WCE images are fed into the machine learning algorithms for classification.

This module has five critical blocks: a convolutional layer, a rectified linear unit, a max-pooling layer, a fully connected layer, and a softmax layer. The convolutional layer utilises the features map to extract all of the features from WCE images. Multiple feature maps are used in this suggested CNN module (DL-CNN) to detect cancer considerably early and more successfully in WCE images. Additionally, numerous filters were utilized to create the feature map. Each filter in this CNN (DL-CNN) module is 5 × 5 × 3 in size and includes appropriate padding.

IV. $\hat{Y} = \varphi(W \times X_{(ij)} + b)$ (1)

V.

X denotes the WCE image's input pixel matrix. $\hat{Y}$ is the output of (DL-CNN). $\varphi(.)$ denotes the activation function of the (DL-CNN). b denotes the base value of (DL-CNN). (DL-CNN) weight are denoted by W.

Table-1. Layer Details of the proposed CNN Architecture

CNN Layers	Kernel Size	Kernel value	Stride	Feature Map
Input	32 x 32 x 3	-	-	1x1860x1
Conv1 +Relu1	5x5x2	64	1	32 x32 x 32
Pooling1	3x3x2	-	2	32x16 x16
Conv2 +Relu2	5x5x2	32	1	32x16 x16
Pooling2	3x3x2			32x8 x8
Conv3 +Relu3	5x5x2			32x8 x8
Pooling 3	3x3x2	-	2	64x4x4
Fully connected1	-	-	-	-
Fully connected2	-	-	-	-

D. Random Forest Classification

Random Forest (RF) is used to classify stomach cancer. By combining bagging and random feature selection techniques, the

random forest generates an ensemble of classifications. Each tree is trained using bootstrap tests against the training data, and predictions are made using the forest's popular votes. While the tree grows, the features are randomly selected at each node.

VI. RESULTS AND DISCUSSION

A. *Hardware Configuration*

In this research, the computer configuration used to execute the software is GPU: NVIDIA GeForce GTX 960; CPU: Intel(R) Core(TM) i5-4660 3.20 GHz. The operating system is Windows 10, and the software configuration includes Matlab and

B. Evaluation parameters

The error rate of the proposed Multi-Layer CNN model is evaluated using three error evaluation methods namely: Mean Absolute Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE). Lower values of (MAE), (MSE), and (RMSE) means the performance of the proposed Multi-Layer CNN model is high. The error evaluation is done using the equations 1, 1, 2 and 3. MAE gives the error statistic of the N samples. It also returns the average of the distances between the estimated and predicted data for N samples. The estimated value is denoted by $\hat{Y}$ and the observed value is denoted by Yi.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Yi - \hat{Y}\right| \qquad (2)$$

MSE gives the average of the square difference between observed data and predicted results.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left|Yi - \hat{Y}\right|^{2} \qquad (3)$$

The standard deviation of the difference between the observed data and estimation data of the proposed model is given by RMSE.

$$MSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|Yi - \hat{Y}\right|^{2}} \qquad (4)$$

The proposed model Multi-Layer CNN is trained using the data set that is divided into three sections: training, validation, and testing.

Table 2 MAE values comparison of the recently published method with Multi-Layer CNN.

Methods	MAE
Faster R-CNN	1.08
SqueezNet	1.56
LBP-GLCM	0.98
SMP-LLC	0.89
Multi-Layer CNN	0.69

Table 3. MSE values comparison of the recently published method with CNN-HCFE-SVM.

Methods	MSE
Faster R-CNN	1.72
SqueezNet	1.62
LBP-GLCM	1.34
SMP-LLC	1.18
Multi-Layer CNN	1.19

Table 4 RMSE values comparison of the recently published method with Multi-Layer CNN.

Methods	RMSE
Faster R-CNN	1.11
SqueezNet	1.43
LBP-GLCM	0.99
SMP-LLC	0.92
Multi-Layer CNN	0.81

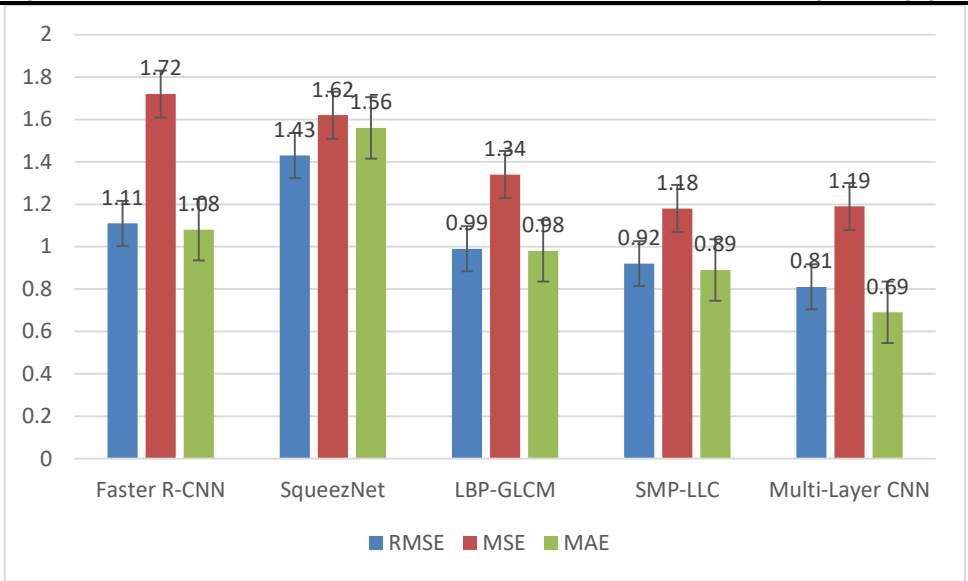


Figure 3: MAE, MSE and RMSE values comparison charts of recently published methods with Multi-Layer CNN.

C. Performance metrics and accuracy evaluations

The cancer detection system proposed here is tested using standard accuracy metrics together with Recall (R), F1-Measure (F1-M) and Precession (P). The essential accuracy variables True Positive, True Negative, False, and False Negative determine the Performance metrics such as Precession (P), Recall (R), and F1-Measure (F1-M). If the stomach cancer detection system's FP and FN rates are low, the prediction and accuracy are excellent.

True Positive Stomach Cancer Detection ($\mathrm{TP_{SCD}}$): It represents the state of accurately predicting cancer by DL- Multi-Layer CNN model.

True Negative Stomach Cancer Detection ($\mathrm{TN_{SCD}}$): It is used to represent the situation of predicting the Cancer-free area successfully by the Multi-Layer CNN model predicts the Cancer-free area successfully.

False Positive Stomach Cancer Detection (FP_{SCD}): It represents the situation when the Multi-Layer CNN model fails to predict cancer appropriately.

False Negative Stomach Cancer Detection (FN_{SCD}): The Multi-Layer CNN model does not reliably estimate the area free of Stomach Cancer, it is referred to as false Negative Stomach Cancer Detection.

The accuracy rate of the proposed Multi-Layer CNN based Stomach Cancer Detection is calculated using Formula 16.

$$Accuracy = \frac{TP_{SCD}+TN_{SCD}}{TP_{SCD}+TN_{SCD}+FP_{SCD}+FN_{SCD}} \quad (5)$$

The precession rate for the proposed Multi-Layer CNN based Stomach Cancer Detection approach is determined using Formula 17.

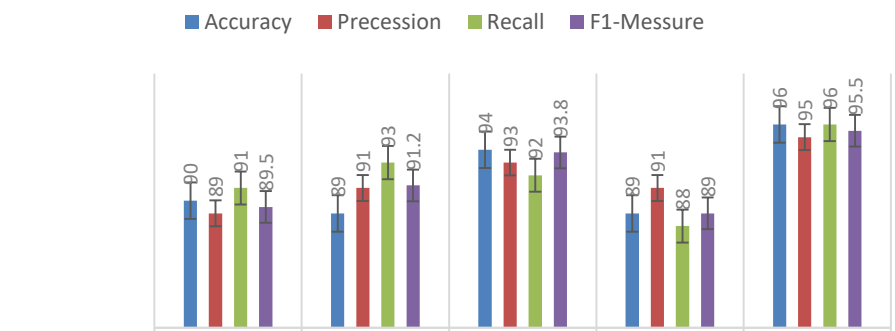
$$P = \frac{TP_{SCD}}{TP_{SCD}+FP_{SCD}} \quad (6)$$

Formula 18 is used to determine the recall rate for the proposed Multi-Layer CNN based Stomach Cancer Detection method.

$$R = \frac{TP_{SCD}}{TP_{SCD}+FN_{SCD}} \quad (7)$$

The proposed Multi-Layer CNN based Stomach Cancer Detection method's F1-Measure is calculated using formula 19.

$$F = \frac{2(P \times R)}{P + R} \quad (8)$$



	Faster R-CNN	SqueezNet	LBP-GLCM	SMP-LLC	Multi-Layer CNN
Accuracy	90	89	94	89	96
Precession	89	91	93	91	95
Recall	91	93	92	88	96
F1-Messure	89.5	91.2	93.8	89	95.5

Figure 4: An accuracy comparison chart of the Multi-Layer CNN.

D. Discussion

Comparative analysis of the proposed method and recently developed stomach cancer detection methods based on the values of MAE, MSE and RMSE are shown in Figure 3. Lower values of MAE, MSE and RMSE mean training efficiency is better. It is proved through experiments that the training efficiency of the proposed method is better. The precession rate of the Stomach cancer detection method based on proposed Multi-Layer CNN and the recently developed deep learning-based methods is depicted in figure 4. It is clear from figure 4 that the proposed approach obtains the maximum precession rate of 97%. Figure 5 also shows the recall comparison of stomach cancer detection between the Multi-Layer CNN to newly developed cancer detection methods. The comparison results reveal that the proposed method gives a better precession rate and a better recall rate of 95. The technique suggested here has a shallow FN rate because of the low precession rate. Comparison of the F1-Measure of stomach cancer detection method presented here that is Multi-Layer CNN, is shown in Figure 5. F1-Measure is beneficial when precession and recall rates are high. The method proposed here produces the highest F1-Measure of 95.5 %.

V.CONCLUSION

It is understood that one of the significant causes of death in India and worldwide is stomach cancer. It is estimated that about two-thirds of total cancer patients suffer from stomach cancer cases. Endoscopy is helpful to clinicians as it enables them to assess the gastrointestinal tract. However, there are certain limitations towards maintaining accuracy in the diagnostic results mainly because of the limited experience of the physician. Secondly, due to the GI tract's complicated environmental circumstances. Nowadays, deep learning has a vital role in medical domains This paper presents a hybrid method for early detection of stomach cancer using convolutional neural networks (CNNs) and machine learning. The WCE images texture features are extracted using a Multi-Layer CNN. The proposed Machine learning approach RF is used to classify cancer and non-cancer images. The classification accuracy of the proposed Multi-Layer CNN approach is achieved to be 96%.

.

References

[1] Shichijo, S.; Endo, Y.; Aoyama, K.; Takeuchi, Y.; Ozawa, T.; Takiyama, H.; Matsuo, K.; Fujishiro, M.; Ishihara, S.; Ishihara, R.; et al.Application of convolutional neural networks for evaluating Helicobacter pylori infection status on the basis of endoscopic images. Scand. J. Gastroenterol. **2019**, 54, 158–163.

[2] Li, L.; Chen, Y.; Shen, Z.; Zhang, X.; Sang, J.; Ding, Y.; Yang, X.; Li, J.; Chen,M.; Jin, C.; et al. Convolutional neural network for the diagnosis of early gastric cancer based on magnifying narrow band imaging. Gastric Cancer. **2020**, 23, 126–132.

[3] Zhang, X.; Hu,W.; Chen, F.; Liu, J.; Yang, Y.;Wang, L.; Duan, H.; Si, J. Gastric precancerous diseases classification using CNN with a concise model. PLoS ONE **2017**, 12, e0185508.

[4] Hirasawa, T.; Aoyama, K.; Tanimoto, T.; Ishihara, S.; Shichijo, S.; Ozawa, T.; Ohnishi, T.; Fujishiro, M.; Matsuo, K.; Fujisaki, J.; et al. Application of artificial intelligence using a convolutional neural network for detecting gastric cancer in endoscopic images. Gastric Cancer **2018**, 21, 653–660.

[5] Sakai, Y.; Takemoto, S.; Hori, K.; Nishimura, M.; Ikematsu, H.; Yano, T.; Yokota, H. Automatic detection of early gastric cancer in endoscopic images using a transferring convolutional neural network. In Proceedings of the 2018 40th Annual

International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 18–21 July 2018; pp. 4138–4141.

[6] Shibata, T.; Teramoto, A.; Yamada, H.; Ohmiya, N.; Saito, K.; Fujita, H. Automated Detection and Segmentation of Early Gastric Cancer from Endoscopic Images Using Mask R-CNN. Appl. Sci. **2020**, 10, 3842.

[7] Shankleman J, Massat NJ, Khagram L, et al. Evaluation of a service intervention to improve awareness and uptake of bowel cancer screening in ethnically-diverse areas. Br J Cancer. 2014;111(7):1440-1447. doi:10.1038/bjc.2014.363.

[8] Raine R, Moss SM, von Wagner C, et al. A national cluster-randomised controlled trial to examine the effect of enhanced reminders on the socioeconomic gradient in uptake in bowel cancer screening. Br J Cancer. 2016;115(12):1479-1486. doi:10.1038/bjc.2016.365.

[9] Li SJ, Sharples LD, Benton SC, et al. Faecal immunochemical testing in bowel cancer screening: Estimating outcomes for different diagnostic policies. J Med Screen. 2021;28(3):277-285. doi:10.1177/0969141320980501.

[10] Koprowski R. Overview of technical solutions and assessment of clinical usefulness of capsule endoscopy. Biomed Eng Online. 2015;14:111. Published 2015 Dec 1. doi:10.1186/s12938-015-0108-3.

[11] Mitselos IV, Christodoulou DK, Katsanos KH, Tsianos EV. Role of wireless capsule endoscopy in the follow-up of inflammatory bowel disease. World J Gastrointest Endosc. 2015;7(6):643-651. doi:10.4253/wjge.v7.i6.643.

[12] Fornaroli F, Gaiani F, Vincenzi F, et al. Applications of wireless capsule endoscopy in pediatric age: an update. Acta Biomed. 2018;89(9-S):40-46. Published 2018 Dec 17. doi:10.23750/abm.v89i9-S.7957.

[13] Alaskar H, Hussain A, Al-Aseem N, Liatsis P, Al-Jumeily D. Application of Convolutional Neural Networks for Automated Ulcer Detection in Wireless Capsule Endoscopy Images. Sensors (Basel). 2019;19(6):1265. Published 2019 Mar 13. doi:10.3390/s19061265