

Development of Polyp Detection Technology by Analyzing Deep-learning

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Abstract

This paper proposes a technique of guiding a clinician by recognizing colon polyp in patients in real time at the time of endoscopic examination. Automatic recognition of colon polyp by endoscopic image has applied Res-net's advanced technique for calculating weight, existing deep learning method to enhance accuracy of recognizing colon polyp. Drawn result values provides information on shape of colon polyp guiding whether there is colon polyp and location of colon polyp in real time. Dataset used in developing analysis technique was collected from 5,000 cases from normal group and 5,000 cases from patients with colon polyp. For verification, accuracy was drawn by calculating confusion matrix with 10-fold cross validation. Accuracy of proposed technique was verified by drawing AUC of 0.96. Dataset was tested with data from control group and patient group in the ratio of 50%. We plan to develop deep learning technique that calculates the ratio of risk of occurrence of colorectal cancer. It is important to secure various test data such as images of colon polyp by type and whether there is adenocarcinoma. We plan to develop service that can predict ratio of risk of occurrence of colorectal cancer by applying relevant techniques automatically.

Keyword : Endoscopy Image, Colon Polyp, Colorectal Cancer, Res-net, Adenocarcinoma

1. Introduction

Amid an opportunity to detect a change in physical body or risk factors of specific diseases increasing due to a rise in an interest in health and improvement in medical technology, frequency of detecting colorectal cancer through medical checkup tends to increase [1][2]. Colorectal cancer, typical western type carcinoma ranks second in cancer mortality. In South Korea, occurrence of colorectal cancer has increased sharply every year along with a change in living environment and dietary life. In South Korea, crude incidence rate of colorectal cancer in 2012 stood at 51.7 cases per 100,000 people accounting for 12% of all cancers. Occurrence of colorectal cancer among male is 15,612 annually ranking second in cancers among male while occurrence of colorectal cancer among female is 10,170

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cases annually ranking third in cancers among female [3]. Korean government has had expense spent in examining colorectal cancer covered by national health insurance since 2018 allowing people aged over fifty who are subject to medical checkup on colorectal cancer to receive medical checkup on colorectal cancer (fecal occult blood test) free of charge. Importance of early medical checkup for preventing colorectal cancer has increased.

Lots of studies that combined IT with medical science have been conducted. For deep learning technology, rapid development of computing power such as GPU has led a great advance in diverse fields including voice recognition, natural language processing, language translation, recognition of things in image, robot engineering and automatic driving. Medical field also has achieved a lot of study results. Lots of studies on diagnosis, prediction and management of cancer have been made. This paper aims to develop a program that is helpful in diagnosing colorectal cancer which shows high occurrence among cancers. This technology can be used for endoscopic diagnosis guide system which is helpful as aids in diagnosing colorectal cancer through endoscope in real time and can process detection of colon polyp in real time. In order to develop relevant technology, we conducted studies and tests with about 10,000 endoscopic image data with combining Res-net based deep learning method. This study is to support diagnosis with high accuracy by combining deep learning technology which has high demand in actual medical field. Contents of proposed method will be described in detail in each chapter.

2. Related Work

2.1 Studies on CNN based object detection

Under the influence of high performance hardware(GPU) and Big Data, various studies in the field of medical science which applied image recognition, voice classification and recognition and object detection through deep learning whose performance has proved in the field of machine learning have been made. Among them, CNN(Convolution Neural Network) [4] which is basically used in the field of image recognition is a deep learning model proposed to overcome problems of overfitting, convergence of local optimum and vanishing gradient through structure of existing artificial neural network. In order to recognize cursive, Lecun [5] composed a black-and-white writing image in 32x32 sizes, and configured 10 numbers as outputs after entering the model, but it did not receive much attention due to the long-term learning problem. High performance hardware and development of bigdata have allowed CNN's speed to improve greatly. It is easy to collect data needed for supervised learning and unsupervised learning such as ImageNet [6], Flickr [7] providing picture sharing service, and INRIA

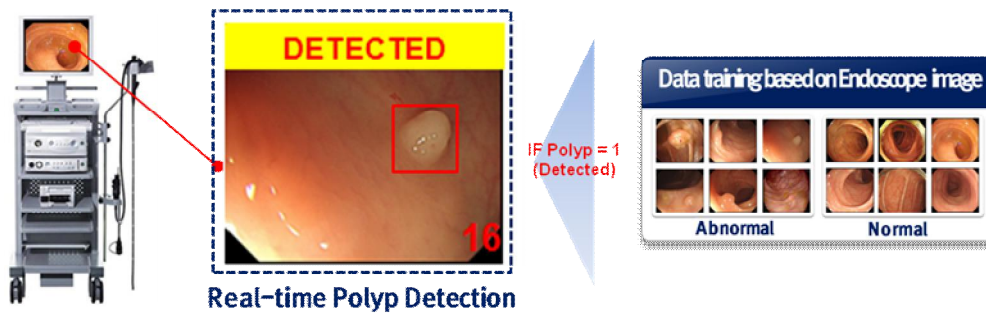
Person dataset [8]. Introducing algorithm presented in [9] about existing overfitting problem has led lots of problems to be solved showing excellent performance in object classification and detection. Unlike existing object detection and learning method, CNN is excellent in automatically creating features over input image and has an advantage that feature extraction and learning are made in one structure.

2.2 R-CNN

R-CNN, Regions with CNN features performs Affine imagewarping in each study area as one of area based deep learning technique and then use selective search to create region proposal. Selective search algorithm [10] based on bottom-up approach amalgamate or removes areas by measuring similarity over each area. R-CNN extracts 227×227 feature vector through CNN structure from learning area which performed selective search algorithm and then classifies it by using linear independent SVM(Support Vector Machine) [11]. R-CNN has an disadvantage that has complex structure and creates 2,000 candidate area to verify each area leading to increased amount of calculation as it provides CNN structures as many as learning areas and problems of image deformation and loss because it affine image warps and crops each learning area in input image.

3. Development of Res-net based Real-time Polyp Detecting Technique

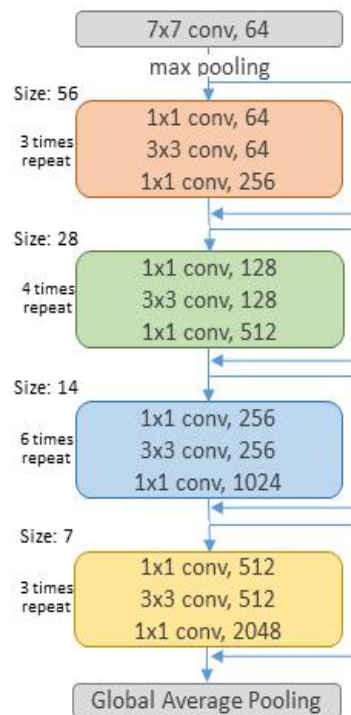
In this paper, colon polyp detecting technique was developed by proposing a method based on Resnet-50 [12] based on deep learning technique which extracts and guides location of colon polyp automatically at the time of diagnosing it by means of endoscope in real time. Concept of developing algorithm proposed in this paper is shown in [Fig. 1].



[Fig. 1] Conceptual Diagram of Real-time Polyp Detection Technology

3.1 Resnet-50 based colon polyp recognizing technique

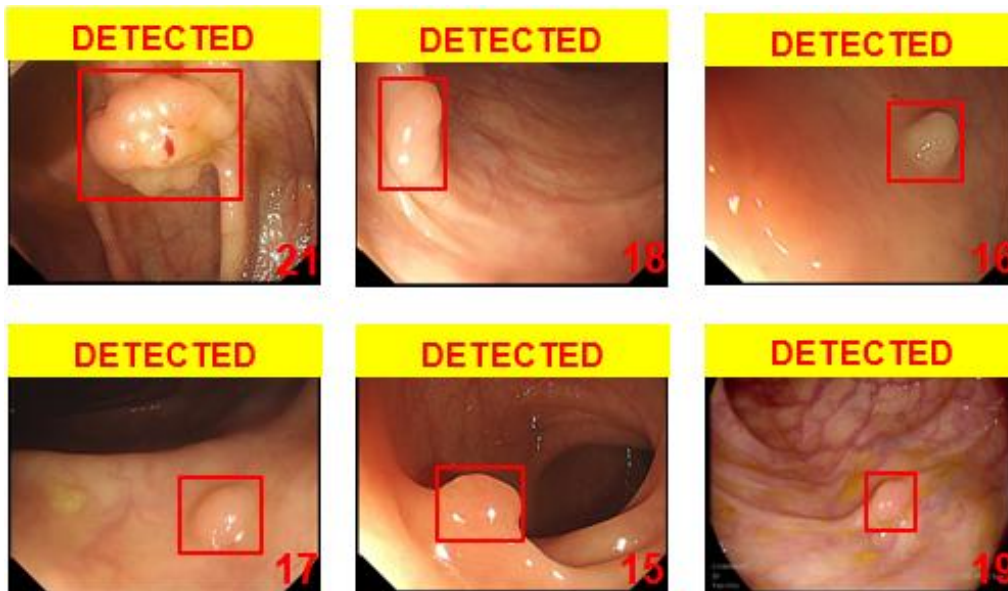
Compared with traditional object division and identification method, a system using deep convolutional neural network(DCNN) called AlexNet [13] shows remarkable recognition performance to trigger studies on deep neural network. It is because the system can extract features of low level, medium level, high level by accumulating CNN' basic structure as CNN's depth and width increase, recognition performance is expected to be improved. However, as neural network's depth and width increase, a problem of increased number of parameters and amount of operation for learning should be solved. GoogleNet [14] introduced inception module which big neural network are connected sparsely to lessen the amount of parameters to be learned allowing neural network to be deepened. ResNet found out that as DCNN' model depth increase, errors in learning process increases, he introduced shortcut connection to minimize such learning errors.



[Fig. 2] Resnet-50 Model applied to Polyp Detection

This method has advantage that can solve a problem of vanishing gradient which means gradient vanishing gradually that becomes back-propagation in learning process because it does not change

structure of existing network significantly, the number of parameters to be learned does not increase even if DCNN's depth deepens. It is because partial learning in each residual block consisting of two to three layers is made not optimizing weight over the whole neural network [15]. ResNet50 model is deep learning method having fifty convolution layers intending to enhance performance of polyp detection by learning ImageNet weight learned with data of over 3 million real life images. ResNet50 model resizes images with size of 512x512 that can process images in real time and performed image pre-processing which reconstructs the scope of pixel (-128 ~ +128) and made images transformed (enlargement, reduction, rotation and shift of images) at the time of learning to be adapted to various changes. Learning parameters consisting of epoch number: 100, batch size: 12, Learning rate: 0.001 ~ 0.00001, anchor size: (32, 64, 128, 256, 512), anchor ratios: (0.5, 1, 2), anchor scales: (1, $2^{1/3}$, $2^{2/3}$) were learned. [Fig. 2] shows a structure of Resnet-50 which was applied to actual polyp detection. [Fig. 3] shows a sample which is a result of applying Resnet-50 algorithm.

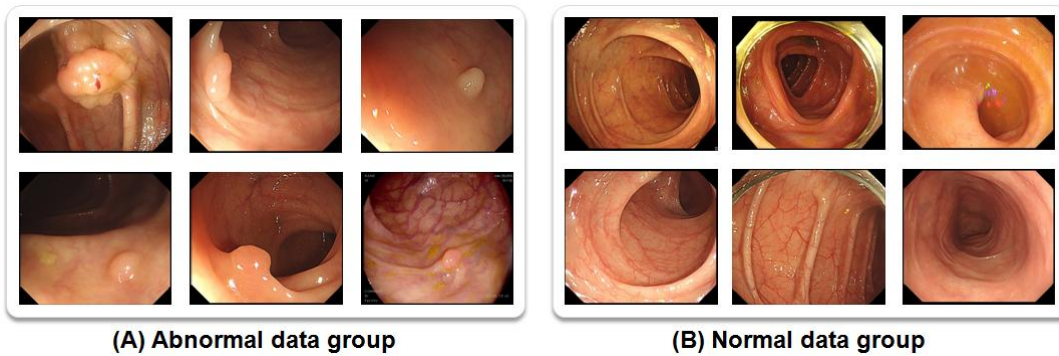


[Fig. 3] The Results of Polyp Detection based on Resnet-50

4. Evaluation of Performance

In order to evaluate performance of proposed method, learning was conducted through 500 data from patients with colorectal cancer and 500 image data from control group. ROI labeling was performed to

apply polyp areas of patient data to Resnet-50 at the time of learning. For evaluation of performance, proposed method was compared with Ground truth that is clinical result and guide.



[Fig. 4] The Samples of Experiment Date for Polyp Detection Method

[Fig. 4] shows verification of experimental data. Experimental data were displayed as sample data classified as normal and abnormal to recognize whether there is colon polyp in terms of learning data. True Positive(TP), False Negative(FN), and False Positive(FP) were drawn by carrying out 10-fold Cross Validation with only still images collected. 10-fold Cross Validation: a total of 10,000 images were divided into ten equal parts. Deep learning model was learned by using nine equal parts and remaining one part was used for a test. A total of ten results were produced changing tested parts and learned parts.

- TP: A case that Intersection Over Union(IoU) value is 0.3 or more between location of ground truth polyp and location of polyp detected by deep learning model on abnormal image.
- FP: A case that Intersection Over Union(IoU) value is less than 0.3 between location of ground truth polyp and location of polyp detected by deep learning model on abnormal image. Or a case that deep learning model detected polyp on normal image.
- FN: A case that Intersection Over Union(IoU) value is less than 0.3 between location of ground truth polyp and location of polyp detected by deep learning model on abnormal image.

[Fig. 5] Definition of Confusion Matrix for Determination of Polyp Recognition Accuracy

According to [Fig. 5], the confusion matrix is defined and described. The corresponding result value is determined based on the IoU value of 0.3 and sensitivity can be calculated based on TP, FN information. Sensitivity was calculated by using produced TP, FP, FN. This is calculated through the following formula (1).

$$\text{Sensitivity} = \text{TP}/(\text{TP}+\text{FN}) \tag{1}$$

In TP, FP, and FN, even the result of final sensitivity can be verified as drawn in [Table 1]. Detected sensitivity result showed 0.96 on average verifying high level of recognition accuracy. In cases that some FP were detected a lot or in cases that information on bubble part, boundary and greyscale was obscure much, wrong results were drawn. A study on weight optimization is needed to lessen relevant FP.

[Table 1] Performance Evaluation Results of Cross Validation

CV	TP	FN	FP	Sensitivity
1	428	15	240	0.962
2	421	22	125	0.948
3	426	19	165	0.956
4	422	15	310	0.964
5	431	20	275	0.952
6	428	13	232	0.974
7	426	15	267	0.969
8	421	11	303	0.977
9	415	25	210	0.945
10	429	13	249	0.971
Total	4,247	168	2,376	0.960

5. Conclusion

This paper was proposed to provide auxiliary guide in real time to medical doctors when implementing endoscopic examination. Proposed information provides location of colon polyp in real time. The method proposed in this paper provides polyp location value by applying colon polyp data and data from general control group to the model using Resnet-50 model. Proposed method was developed to provide a role of auxiliary tool by applying artificial intelligence technology to polyp that shows rapid movement or is likely to miss when clinician conducts endoscopic examination. In order to evaluate accuracy and suitability of developed algorithm, proposed method was compared with clinician's standard. In addition, sensitivity was evaluated through 10 fold cross validation to determine accuracy of recognizing whether there is colon polyp. Evaluation showed that accuracy was over 0.96 which suggests that proposed method is enough to be used as auxiliary tool in diagnosis when a clinician examines a patient. Inaccurate FP results were drawn in case that bubble part, boundary or greyscale information is

obscure a lot. To solve above mentioned problem, additional studies on renewal of optimum value in weight column or additional use of feature information in pre-processing.

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