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DL-BASED AUTOMATIC DETECTION AND CLASSIFICATION FOR ENDOSCOPY

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ABSTRACT

Colorectal polyps are important precursors to colon cancer which is the third most common Cause of cancer mortality for both men and women. Colorectal cancer is one of the leading causes of cancer deaths worldwide. During a colonoscopy, physicians manually inspect the colon of a patient using a camera in search for polyps, which are known to be possible precursors to colorectal cancer. Polyps are known as possible colorectal cancer precursors, and their early detection is of great importance, but highly challenging from an image processing standpoint. In the medical field, Convolutional Neural Networks (CNN's) have become state of the art for many computer visions tasks in recent years. A CNN is very similar to traditional Neural Networks in the sense of being constructed by neurons with their respective weights, biases and activation functions. CNNs have brought about a revolution in computer vision to large annotated datasets, such as ImageNet and Places. CNNs in CNNs are supervised models trained end to end to learn hierarchies of features automatically extracting. Experimental results for this paper show, we can obtain an accuracy over 90% in only 2 minutes by using small dataset with keras augmented data and with only a small CNN. However, no more change in accuracy while we apply transfer learning using pre-trained VGG16.While we obtained around 98% accuracy by apply a fine tuning.

Keywords— artificial intelligence (AI); computer-aided detection; Colonoscopy; deep learning; endoscopy; screening; surveillance; *Convolutional Neural Networks****; polyps;***

I. INTRODUCTION

Colorectal cancer (CRC) is the main reason of cancer-related mortality worldwide. Over the coming decade, CRC burden is expected to increase significantly (Kudo et al., 2019). Colorectal cancer starts by polyps which is protrusions from the colon surface, and it need around 2-5 year to develop to cancer (Tze, 2017). Early detection of polyps is the vital way to the prevention of colorectal cancers (Ponzio, Macii, Ficarra and Di Cataldo, 2018). Therefore, early detection of polyps and cancers is the major goals of endoscopy and colonoscopy. Colonoscopy removal of neoplastic polyps to preventing CRC. However, colonoscopy dependent on operator and still there is Wide variability between endoscopists when considering adenoma detection rate (ADR) (El Hajjar and Rey, 2020). Beyond these, in the endoscopic process the polyps can be missed because it visually subtle and the endoscopist may be overlook it. Add to that, poor concentration and human fatigue are obvious reasons to miss the polyps. Many different solutions are provided to overcome this issue. These include to modify endoscopist behaviors, by demonstrated an improved ADR to recognition pattern of subtle polyps. Moreover, many studies have shown that present of an experienced nurse or an additional observer during the procedures of colonoscopy, it may lead to an increased ADR (El Hajjar and Rey, 2020).

II. CRC SCREENING AND SURVEILLANCE

Colonoscopy is the cornerstone of CRC screening programs (Buczacki and Wheeler, 2016). It can enable the early detection of cancerous lesions or be used as a follow-up to another screening test. Currently, one of the most common screening procedures for CRC is a colonoscopy, where physicians probe for non-cancerous growths referred to as colorectal polyps a possible precursor to CRC. Furthermore, colorectal cancer has also been estimated to be one of the most expensive diseases to treat. The incidence of colorectal cancer (CRC) is increasing worldwide (Ponzio, Macii, Ficarra and Di Cataldo, 2018). CRC has high mortality when detected at advanced stages, yet it is also highly preventable. Given the difficulties in implementing major lifestyle changes or widespread primary prevention strategies to decrease CRC risk, screening is the most powerful public health tool to reduce mortality. Screening methods are effective but have limitations. Furthermore, many screen-eligible people remain unscreened (El Hajjar and Rey, 2020). A quantum step in CRC prevention might come with the development of new screening strategies, but great gains can be made by deploying the available CRC screening modalities in ways that optimize outcomes while making judicious use of resources (Maida et al., 2017).

III. ARTIFICIAL INTELLIGENCE IN GASTROINTESTIANAL ENDOSCOPY

With the incessant advances in information technology, artificial intelligence (AI) algorithms has been interduce to mimics human capabilities (El Hajjar and Rey, 2020). Artificial intelligence (AI) algorithms become the most common technology in medical field that compensate human's limited capability which may altered by fatigue, stress, or limited experience.AI can be the best option for a fast and reliable way to treat the growing number of patients. Artificial Intelligence (AI) can make an excellent decision in medicine and health care by provide physicians with all the information they need. There are many applications of AI technology in gastrointestinal (GI) endoscopy (Kudo et al., 2019). Artificial intelligence has made significant progress owing to the development of deep neural networks and machine learning algorithms, especially in the area of computer vision. The technology of AI has the potential to provide automated detection of colorectal polyps.

DL methods in GI image analysis tasks include image detection, classification, segmentation, recognition, location, and a few other application (Glissen Brown and Berzin, 2020). Many efficient deep DL models have emerged with the development of DL theory (El Hajjar and Rey, 2020). DL technique has been gradually utilized to GI image analysis. However, most of the existing research works are still limited to the detection, classification and segmentation of polyps, DL method requires a large number of labeled training data sets. Due to the high cost of manual labeling by medical experts and the consideration of patient privacy issues, it is difficult to obtain a large amount of labeled medical image data. Unlike to skin images, eye images, MR and CT images which are collected from the body surface, the collection of GI image requires performing an endoscopy, which involves entering a camera probe into the patient's body (Murali and Sivakumaran, 2018). Therefore, the data acquisition of GI image is more difficult, and the application of DL in computer-aided GI diagnosis is severely limited, challenging and nonproductive (El Hajjar and Rey, 2020). Great success has been achieved in the application of DL in other diseases. DL methods can be divided into supervised learning and unsupervised learning methods. Currently, almost all of the deep models used in GI image processing are CNN-based supervised learning networks, only one was based on GANs segmentation. There may be great visual differences among some images of the same disease, and there may also be slight differences among images of different diseases (Greenspan, van Ginneken and Summers, 2016). As a result, different endoscopic experts may give different labels to the same image.

IV. MATERIALS AND METHODS

In this section, the main aim is to introduce a polyp detection system by using small CNN. first step is to use the dataset and extract it to polyps and non-polyps. Next, the dataset is spilt to training and validation for both polyp and non-polyp images. After that by using a small CNNs we build a classifier for polyps/non-polyp images. Main 6 steps of the experiments are:

a) Datasets and data splitting

b) Small CNN classifier
c) Transfer Learning
d) fine tuning of the pre-trained VGG16
e) small CNN to extract polyp using simple Windows

a) DATASETS AND DATA SPLITTING

The original datasets have been collected from two source, first dataset group are downloaded from the link: https://site.uit.no/deephealthresearch/projects/image-based-prediction-and-prevention/ .Second source of dataset is CVC-Colon DB database which has 300 images with resolution of 500 × 574 resolution and are extracted from 13 video sequences from 13 patients. The total dataset of the experiments is around 1,242 images divided in 621 original images and 621 ground truth images, then the dataset is cropped to extract non-polyp images from polyps' images to have total 1,212 images in training the model. The way to crop the original image is by divide the original image into two part, first part is the areas that cover by whole polyps is f extracting as polyps image with a patch (150*150) from every frame (300*300).Seconded part is extract from the area does not have any polyps from the original image. Figure 2 display extracting way form polyps and non-polyps.the input data are splitting in to training and validation by the percentage of 75/25 for train/validate. However, in this experiment we are using 910 datasets for training split to 455 polyps and 455 non-polyps. Also, around 302 images are used in validation section for 151 polyps and 151 non-polyps.

b) SMALL CNN CLASSIFIER

After dataset collection, cropped and splitting, the stage of build small CNN classifier is the next. The CNN_1Conv_1FC model will have the have many characteristics such as: the convolutional layer will used MaxPooling2D and relu activation function, fully convolutional layer also will use relu activation and a dropout = 0.5. while the output layer will use sigmoid activation for classification of polyps / non-polyps.

I. CONVOLUTIONAL NEURAL NETWORK

Convolutional neural networks have been one of the most influential innovations in the field of computer vision. The convoluted neural network consists of alternating layers of convoluted and pooled layers, simulating simple cell and complex cell cascade structures for high-level feature extraction in the visual cortex (Ponzio, Macii, Ficarra and Di Cataldo, 2018). The neurons of the convolution layer respond to a portion of the region of the previous layer and extract the higher features of the input. The neurons of the pooled layer are averaged or maximized for a portion of the input of the previous layer, resisting the slight deformation or displacement. The latter layers of the convoluted neural network are typically a number of fully connected layers and a classifier (Wickstrøm, Kampffmeyer and Jenssen, 2020). The convolutional neural network is a feature-based method and applied to physical recognition. It is different from the traditional artificial feature extraction and the high-performance classifier design for the feature. Convolutional neural networks (CNNs) continue to achieve record breaking accuracy performances on many visual recognition benchmarks across research domains. CNNs are supervised models trained end to end to learn hierarchies of features automatically without resorting to sometimes complicated input pre-processing, output post processing, and feature engineering schemes yielding robust classification and regression performances. The structure of Convolutional Neural Network (CNN) is made up of connected trainable layers build one after another followed by two fully connected layer. The trainable layer is for the purpose of learning the image representation while two fully connected layers are for classification.

IN this stage we apply different structure for the model such as, changing the number of Conv layer, number of filters or epochs to achieve high accuracy of the mode. Table1 show the different model structure that are using in this experiment.

Table 1 different CNN model structure

model	Technology	number of filters	dimension	epochs
Model1-1	CON-FC	32	3*3 pixels	50
Model1-2	CON-FC	32	5 x 5 pixels	50
Model1-3	CON-FC	64	3*3 pixels	50
Model1-4	CON-FC	128	3*3 pixels	50
Model2-1	CON-CON-FC	32	3*3 pixels	50
Model2-2	CON-CON-FC	64	3*3 pixels	50
Model3-1	CON-CON--CON-FC	32	3*3 pixels	50
Model3-2	CON-CON--CON-FC	64	3*3 pixels	50
Model3-3	CON-CON--CON-FC	64	3*3 pixels	100

c) TRANSFER LEARNING

Transfer learning is a method of build new model in a timesaving way from patterns that have been learned when solving a different problem. In deep learning, transfer learning technique used avoid starting from scratch where the first model is trained to solve one problem then this model can be used again to solve another related problem by using one or more layer from the first neural network model. In the part of transfer learning, we apply the transfer learning using pre-trained VGG16. First, we Freeze the bottom part of the VGG16, saved output matrices from bottom VGG16 for training and validation, then the output from the bottom model should save to be use as an input for the trainable model. After that the fully convolutional layers are train, finally saved the best model.

d) FINE TUNING OF PRE-TRUNING VGG16

This part is looking to apply a fine tuning to train 2 convolutional blocks with the FC layer. The initial weights from the previous model will used by FC layer.The process of fine tuning of the pre-trained VGG16 is follow these steps: First ,pre-trained VGG16 should be load as the lower model, keep FC layer as a top model, previous calculated weights for the Fully Convolution layer should load, Freeze a number of convolutional blocks, last best model should save, in the case the accuracy of validation is not increasing in 10 iterations we should use earlystopping, SGD optimizer should use and last using different values for the main hyperparameters to search the best model.

e) SMALL CNN TO EXTRACT POLYP USING SIMPLE WINDOWS

In this section, we apply the small CNN model to the input image with the polyp, then a smaller image is extract with the fragments 150 x 150 x 3 using a sliding window. The best polyp prediction should be used.

V. RESULT AND DISCUSSION

This work is an investigation of polyp detecting from colonoscopy images using small CNN model. We start the experiment with downloaded the dataset from two source, cropped it to extract a polyp and non-polyp and after that we split it to training and validation. Table 2 show the dataset model.

Table 2 dataset model

Original CVC-Colon DB dataset			
Original image		Ground truth image	
612		612	
extract the dataset			
polyps		Non-polyps	
606		606	
split the dataset			
Train		Validation	
910		302	
Patch balanced Dataset for the experiments			
Train75 %		Validation 25 %	
polyps	Non-polyps	polyps	Non-polyps
455	455	151	151

While searching for the best classifier accuracy by using 50 epochs, the accuracy is change by changing some parameters. We obtain the best accuracy around 0.921875 in 100 iterations and by training 3 con layers with 64 batch-size and 3*3 dimensions.

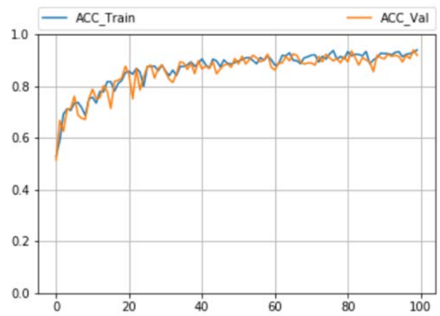

Figure 1 100 iterations and by training 3 con layers with 64 batch-size and 3*3 dimensions

When we used VGG16 transfer learning, there is no better result is obtained in the validation accuracy then the small CNN.

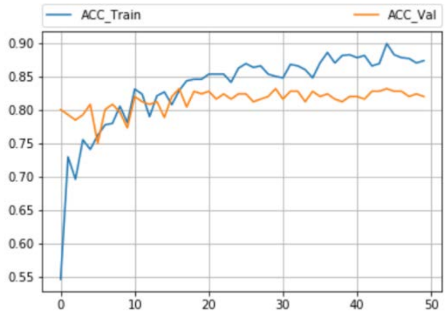

Figure 2 accuracy after applied fine tuning

While we apply fine tuning, the experiment achieves a high accuracy over 98% better then small CNN accuracy over 92%. Also, we expected better result in accuracy if more layer is trained but the overfitting will increase. In the last part of this work, it shown that small CNN and windows sliding algorithm can obtain 90% of accuracy in detect a polyp into a colonoscopy image.

VI. FUTURE DIRECTIONS

The existing prospective studies highlight the increase of artificial intelligence applications in gastroenterology (Greenspan, van Ginneken and Summers, 2016). Integration of artificial intelligence systems with EMR (electronic medical records) and endoscopy platforms will enhance the clinical workflow. To interduce a new AI applications must have the feature of "read in" data from EMR and a video input , thuds to support real time decision and for the purpose of data training (Kudo et al., 2019).As discussed in this review, there are several studies that present the value of AI in term of improve the performance on clinical tasks such as polyps detection. Future studies should continue focus of the AI tools that can improve other clinical tasks such as diagnosing inflammatory bowel disease by using similar methodologies for diagnosis of celiac disease. In additional, new researches should provide mythology to eliminate latency in detection in clinical endoscopy to facilitate applicability of these technologies (Greenspan, van Ginneken and Summers, 2016). Moreover, future research has to understand pragmatic and ethical considerations while integrate the AI tools with gastroenterology practice. Finally, to deployed and design a new system with new technology is need A deeper understanding of the end-user, so physician sentiment toward artificial intelligence is crucial to begin (Wickstrøm, Kampffmeyer and Jenssen, 2020).

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VIII. CONCLUSION

This work is investigating in detecting polyps in colonoscopy image by applying different model. First model is using small CNN classifier with different parameters and show that the accuracy is increase by increasing the number of epochs to reach 92% in 100 epochs. The accuracy rate is not change when we apply transfer learning using pre-trained VGG16 while it achieves better rate when fine tuning is applied. However, the experimental result present that with an accuracy over 90% it is possible to detect a polyp into a colonoscopy image by Using a very simple CNN and windows sliding algorithm.

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