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Original Research Article

Application of Artificial Intelligence Technology in Automatic Detection of large Intestine Polyps

Martin Alonso Gomez-Zuleta[1], Diego Fernando Cano-Rosales[2]*, Diego Fernando Bravo-Higuera[3], Josue Andre Ruano-Balseca[4], Eduardo Romero-Castro[5]

[1] *Gastroenterology and Echoendoscopy Unit. National University Hospital. National University of Colombia, Colombia*

[2] *Gastroenterology, National University of Colombia. National University Hospital. Bogota D.C., Colombia*

[3] *Militar University of New Granada. National University of Colombia. Bogota D.C., Colombia*

[4] *Systems and computing. National University of Colombia. Bogota D.C., Colombia*

[5] *Biomedical Sciences, National University of Colombia. Bogota D.C., Colombia*

ABSTRACT

Objective: to establish an automatic colonoscopy method based on artificial intelligence. **Methods:** a public database established by a university hospital was used, including colorectal fat and data collection. Initially, all frames in the video are normalized to reduce the high variability between databases. Then, the convolution neural network is used for full depth learning to complete the detection task of polyps. The network starts with the weights learned from millions of natural images in the ImageNet database. According to the fine-tuning technology, the colonoscopy image is used to update the network weight. Finally, the detection of polyps is performed by assigning the probability of containing Po´ lipo to each table and determining the threshold defined when polyps appears in the table. **Results:** 1875 cases were collected from 5 public databases and databases established by university hospitals, with a total of 123046 forms. The method was trained and evaluated. Comparing the results with the scores of different colonoscopy experts, the accuracy was 0.77, the sensitivity was 0.89, the specificity was 0.71, and the ROC curve (re ceiver operation characteristics) was 0.87. **Conclusion:** compared with experienced gastrointestinal markers, this method overcomes the high variability of different types of lesions and different colonic light conditions (handle, folding or contraction), has very high sensitivity, and can reduce human errors, which is one of the main factors leading to the non detection or leakage of Po lipids in colonoscopy.

Keywords: *Machine Colonoscopy; Colorectal cancer; Polyp; Screening; Artificial intelligence*

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***CORRESPONDING AUTHOR**

Diego Fernando Cano-Rosales
dfcanor@unal.edu.co;

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1. Introductory

Colorectal cancer is the third largest cancer in the world and the second leading cause of cancer death. In Colombia, it is the fourth most common tumor in men and women, with a higher incidence that increase every year[1,2]. Many studies have concluded that screening for RCC is cost-effective in people at moderate risk (people without family history and susceptibility History). It is well known that age (≥50 years), eating habits and smoking are risk factors for increasing the incidence of this disease. In the general population, the risk is 5%–6%, and the incidence rises sharply from the age of 50. Therefore, people aged 50 or over are considered to be at medium risk, and the screening scheme should be started[3,4].

As for the survival rate of RCC patients, it is directly related to the severity of the disease at the time of diagnosis. Individuals diagnosed with advanced stage had a survival rate of 7% within 5 years, while

92%[5] of patients with early RCC were reported; Therefore, early detection of tumors, or more precisely, detection of adenomatous (precancerous) polyps, so as to prevent disease, is of great significance. It is well known that using existing screening techniques (occult blood, colonoscopy), RCC can be highly prevented in more than 90% of cases.

Many studies have shown that colonoscopy is the first choice for the prevention and early detection of RCC because, as mentioned above, it can detect the main sources of RCC, such as adenomatous polyps[6-9].

In addition to early detection of cancer, if timely treatment is completely curable, polyp detection is a quality indicator of colonoscopy, and 20% of women and 30% of men are considered to be an indicator of adenomatous polyps (with high cancer risk) during the examination; This means that an average of 25% of colonoscopy should find adenomatous polyps. Unfortunately, different studies report that about 26% of polyps are not found during colonoscopy, which is a very high error rate, which is mainly explained by two factors: the number of blind spots in colonoscopy (lipid behind folds, colon stalk, preparation, etc.) And human errors ience affecting the smoothness of colon scanning. At present, some strategies have solved this challenge as a classification task and used machine learning technology.

On the one hand, some authors try to screen liposome candidates from low-level characteristics. Bernal et al.[13] proposed an appearance model of polyps, which describes the polyps valleys as a continuous and concave boundaries. This feature is used to train the classifier, which obtains a polyps detection sensitivity of 0.89 in a test set (test). Shin et al.[14] proposed a block by block classification strategy, using the combination of shape and color features to obtain a sensitivity of 0.86. On the other hand, some studies use deep convolutional neural network (CNN), which is a set of rhythms gathered at the end of *deep learning*. Urban et al.[15] proposed a convolution network for real-time detection of liposomes of different sizes, with a sensitivity of 0.95. However, Taha and cola borators[16] analyzed some limitations of these works, one of which is that these works related to surgery[10-12]. A lot of work has been done to try to solve these two factors to reduce the rate of fat loss, which is why people have designed some accessories to enable the fat hidden behind the folds to be identified, such as hats, cuffs, and even a micro endoscope called the "*third eye"*, which tries to flatten the folds or see the back of the folds. In addition, it has recently been considered that the factors related to human errors can be mitigated at least by introducing a second reader (computers). In this case, technology and artificial intelligence begin to display results, which can significantly improve the detection rate of polyps and allow the number of undetected polyps in gastrointestinal units to be reduced.

Developing computational strategies for pattern extraction and automatic detection of colorectal fat in colonoscopy video is a very complex problem. The video of colonoscopy is recorded in a large number of noise sources, which are easy to cover up the lesions; For example, the gloss on the intestinal wall caused by reflective light source or specular reflection, the movement of organs and intestinal secretions blocking the field of view of colonoscopy, and expert exper

require a lot of data for training. In addition, these databases are obtained under specific climatic conditions; In particular, imaging equipment, scanning protocols executed by experts and the extraction of sequences vulnerable to visual damage. Although some progress has been made, there is still a challenge to develop generalizable models to accurately detect lesions, regardless of the type of injury, the form of expert scanning or the colonoscopy unit used.

The main purpose of this study is to establish a strategy for automatically detecting colorectal polyps. It is suggested to construct a second reader to support the colon scanning process and reduce the number of undetected lesions in the process of settler replication. This paper presents an automatic classification strategy of polyps in colonoscopy video sequence. This study is based on a rhythmic in-depth learning and evaluates the different architectures of convolutional networks. The tissue structure of this paper is as follows: firstly, the automatic detection

method of polyps is introduced; then, it describes the policy considerations surrounding this work; then, the experimental configuration is displayed together with all test results and compared with expert notes; then it introduces the discussion of this paper; Finally, the conclusion is drawn and the future work is put forward.

2. Methodology

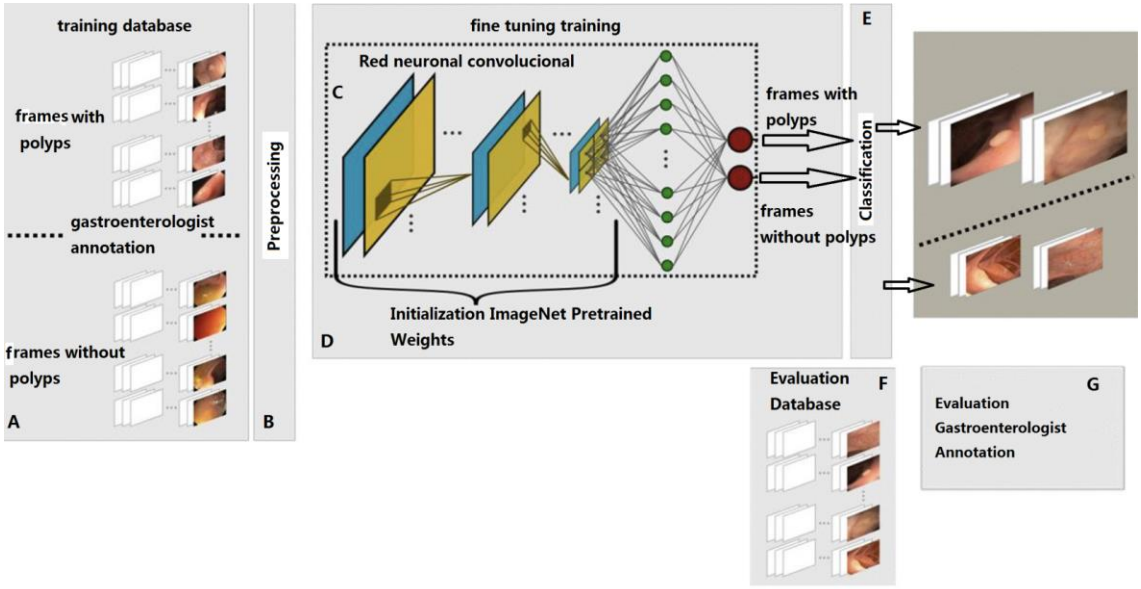

Figure 1. Method for automatic detection of polyps. First, it integrates an annotated colonoscopy video database (**A**). Each of these tables is preprocessed (**B**) to feed back some CNN based models (**C**). This model is fine tuned and trained with the preset weights of millions of natural genes (**D**). In the trained network, the test database (**F**) was used **to** evaluate its performance in detecting polyps**(H),** and the results were compared with expert note (**G**).

This paper introduces a deep learning method that simulates the high variability in the process of colonoscopy. This method aims to automatically detect the lipids in the process of colonoscopy. This task is divided into two stages: training and classification. Firstly, frame-by-frame preprocessing is performed, common to both stages the two eta-pas are preprocessed table by table and generally. Then, convolutional neural networks were trained using a large number of colonoscopy images annotated by colonoscopy experts (with about 20 years of experience and 50 thousand000 colonoscopy examinations), which were divided into two categories: negative class or without polyps *Po´* lipo, positive class or with polyps*Po´* lipo. The model obtained from the learning process is used to classify new genes (or not used in the naming process) into one of these two categories. The process of this work is shown in **Figure 1**, as follows.

3. Acquisition protocol and preprocessing

In order to reduce the influence of various noise sources on different colonoscopy acquisition processes and colorectal physiological conditions, it is necessary to preprocess the video frame by frame. Firstly, each frame is normalized with an average value of 0 and a standard deviation(SD) of 1, so that the features extracted between frames are comparable. Then, capture presents different spatial resolutions according to different shooting devices, so each frame is scaled to 300 x 300 pixels so that each frame has the same capture grid.

4. CNN architecture

The main unit of these structures is neurons, which provide output as a function of input. The arrangement of neurons forms a layer or block, and the network is composed of multiple basic blocks. These basic blocks are arranged in the following

order: multiple pairs of layers with volume (**Figure. 1C**, blue table) and clustering layers (**Figure. 1C**, yellow table), which provide the feature vector of the image, Then there is a set of fully connected layers **(Figure 1C**, green circles), which is used to calculate the probability that a set of features belong to a certain class, and ends with the activation layer (**Figure 1C**,red circles**).** In the activation layer, the obtained probability is normalized and the required binary classification is obtained. The functions of these blocks are:

- Convolution layers: recognize the local features in the whole image, such as the pattern of shape, edge and texture, which is very important to describe the image. This layer connects a subset of adjacent pixels of an image or neuron to all nodes of the first convolution layer. One of the convolution layers or cores is distinguished by the specific weight of each node; by operating on a specific area of the image, it provides a feature map of the area.
- Pooling layers: reduce the computational complexity, so as to reduce the amount of features in the convolution layer, and obtain the hierarchical set of image feature mapping.
- Fully-connected layers: This layer connects each of the neurons in the previous layer to each of the neurons in the next layer. The previous layer is a flat or vector representation of the obtained feature maps. The number of neurons in the next layer is determined by the number of classes that are required to be classified. Finally, the fully connected layer provides a vote
- Activation function: normalizes the probabilities obtained from the completely connected layers according to a specific function, in which a probability of 0 to 1 is obtained.

A particular architecture is made up of an array of modules that contain different configurations and orders of the fundamental blocks explained above, and the result obtained by each neuron is known as a gradient. Three architectures highly evaluated and validated in the state of the art were used in this work: InceptionV3, Vgg16 and ResNet50. Next, we describe each one of them.

- Inception V3: composed of 48 floors, 24 million feet. To a large extent, these layers are divided into 11 levels, and the features of multiple levels are extracted on these levels. Each module consists of a given convolution and grouping layer structure, which is rectified by *linear rectifier unit* (ReLu) function. It ends with an activation function called *exponential normalization* (softmax)[17].
- Vgg16: 16 floors in total, 138,000 meters. 13 layers are convoluted, one layer is clustered (in some cases), the two layers are completely connected, and finally the normalized exponential activation function. This structure is famous for using a small filter of size 3 x 3 on the convolution layer. It has lower computational costs than most architectures[18].
- RESNET 50: composed of 50 floors, 26 million feet. This structure is constructed under the concept of residual network. Obviously, in such a very deep area, the gradient of propagation will disappear in the last layer. To verify this, some layers are trained using the gradient residuals obtained at this point and the gradients at the previous two positions. This structure ends with a standardized exponential activation function[19].

5. Fine tuning training

The high performance of classification mainly depends on the number of IMA genes and how to start training the weight of CNN. Colonoscopy has about 12,000 frames per video, so the availability of databases with IMA gene annotation is limited. Then, the limited data is used for training, and the network weight is started randomly as usual, resulting in the failure of the training process. In order to avoid this uncertainty, we use the weights of the same type of networks (*transfer learning*), which have previously been trained for another natural gene classification problem, and the database contains a large number of unprocessed genes. The reason for this is that even if natural genes and genes in colonoscopy are different, their statistical structures are similar,

and they are composed of original genes representing objects. In this case, networks trained to recognize objects in natural genes are used as the initial conditions for training these networks to recognize polyps.

The use of these weights is achieved through a process called fine tuning. For this purpose, the whole pre focus network is removed and the last fully connected layer is removed. This layer is replaced by a new layer, which has the same number of neurons as the number of classes in the classification task (polyp-on polyp) and starts from the weight of the pretained network. Then, the last layer is trained first, and then the weights of the other layers of the network are updated in the iterative process; this approach is known as backpropagation. Each iteration of this training is carried out using a certain number of samples or batches of the training images. At the end of this process, all sample sets of the network are trained, which is called the training epoch. Determine the number of epochs according to the complexity of the samples to be classified. Finally, when the probability of a training image is high and consistent with the labeled label, the training reaches a climax.

6. Polyp detection

Using the trained network model, it is applicable to a set of evaluation videos, in which a label is classified and assigned: (1) Tables with and (0) without the presence of polyps. However, there are also some surfaces with structures similar to fat, such as burrs produced by intestinal fluids. In these tables, the model shows a classification error and regards this table as a lesson. By temporarily analyzing these errors, it is worth noting that they are displayed as outliers (3 to 10 frames) in a small window of time (60 frames or 2 seconds). Therefore, the classification conducted by the network is temporarily filtered, and it is determined that if at least 50% of the 60 consecutive tables are classified without polyps, the remaining four tables are filtered and assigned a new label, such as the table without polyps. Finally, a polyp is detected when the proposed method classifies an image as a box with a polyp present or a positive class.

7. Data base

The database construction in this study was designed to capture the maximum variability of colonoscopy pretreatment. In order to train and evaluate the proposed method, we collected sequences from different gastrointestinal centers, which contain different types of polymorphic and non polymorphic lesions (morphology and colon location), scanning and capture devices of different experts. The following are the details of these databases.

7.1. ASU Mayo clinical colonoscopy video database

The equipment was built in the gastroenterology department of Mayo Clinic in Arizona. It consists of 20 colonoscopy sequences, which are divided into 10 sequences with polyps and 10 sequences without polyps. These notes were performed by gastroenterology students and verified by experts. This collection is widely used in the latest technology and serves as a database for the “2015 ISBI Grand Challenge on Automatic Polyp Detection in Colonoscopy Videos”[20].

7.2. CVC-ColonDB

It consists of short sequences of 15 different lesions, with a total of 300 frames. This set of lesions is highly variable and difficult to detect because they are very similar to healthy areas. Each painting has an expert gastrointestinal sign. The church was built at the Clinical Hospital of Barcelona, Spain[13].

7.3. CVC-ClinicDB

It consists of 29 short sequences with different injuries that bring together 612 frames annotated by an expert. This database was used by the MICCAI 2015 Sub-Challenge on Automatic event training set Polyp Detection Challenge in Colonoscopy Videos. This collection was built at the Clinical Hospital of Barcelona, Spain[21].

7.4. ETISLarib Polyp DB

It has 196 images, and each gene has an expert annotation. The database is used for the test set of MICCAI 2015 Sub-Challenge on Automatic Polyp Detection Challenge in Colonoscopy Videos[22].

7.5. Kvasir dataset

It is a database that was collected using endoscopic equipment at Vestre Viken Health Trust (VV), in Norway. The images are annotated by one or more medical experts from VV and the Norwegian Cancer Registry (CRN). The data set consists of the images with different resolution from 720 x 576 up to 1920 x 1072 pixels[20].

7.6. HU-DB

This collection was built at the University Hospital of Bogota. There are 253 colonoscopy videos, a total of 233 lesions. Each frame was recorded by a colonoscopy expert who had about 20 years of experience and performed 50,000 colonoscopies.

Each video is shot at 30 frames per second with spatial resolutions of 895 x 718, 574 x 480 and 583 x 457. A total of 1875 cases, 48,573 cases of polyps and 74,548 cases without polyps were integrated into the case database. Each frame of these videos was rated positive by experts. If there is fat, it is positive. If there is no fat, it is negative. **Table 1** summarizes the number of videos and tables for each database used in this study.

Table 1. Describe the number of colonoscopy videos or cases and video frames in each database used in this study*

Data base	Video only		Surface	
	polyp	Polyp free	polyp	Polyp free
ASU-Mayo	10	10	4683	13,481
CVC-ClinicDB	29	0	612	0
CVC-ColonDB	15	0	379	0
ETIS	28	0	196	0
Kvasir	1000	500	1000	500
HU	233	50	41,70	60,567
Total	1315	560	48,57	74,548

*Merging multiple databases to train and evaluate the proposed method can cover a wide range of damage variability.

8. Policy considerations

This work is carried out in accordance with resolution °008430 of 1993, which sets out the scientific, technical and administrative standards for human research (article 11). The project is classified as the least risky research because it only needs to use digital genes, which are generated from anonymously copied colonoscopies videos; in other words, there is no way to know the name or identity of the research object.

9. Result

The CNN used in this article includes InceptionV3, Rresnet50 and Vgg16. The labels assigned to each network were compared with the notes reassigned by experts in each table. The following experimental configuration and evaluation methods are applied to each of the architecture.

9.1. Experimental configuration

CNN previously was trained with images from the public ImageNet database, which contains about 14 million natural images. The resulting weights are used to start a new colonoscopy numerical training process by fine-tuning method. All this updated the weights and trained the network with the settler replica database. The weight update is carried out in the whole training set, with only 120 epochs. Each epoch will train the model through a batch of 32 frames until it covers all frames. For each network, the decision threshold is set manually to maintain a balance in the classification or unpacking of the two categories. The training program is that 70% of the database is used for training and 30% of the database is used to verify the number of cases; In other words, the data is separated from the beginning, and the training, verification and test data are never mixed. A total of 213 cases (24,668 frames) of polyps and 36 videos (27,534 frames) were trained and verified. The evaluation was performed with 103 videos (23,831 frames) and 25 videos (47,013 frames). The details of this set are shown in **Table 2**.

9.2. Quantitative evaluation

The proposed method automatically detects polyps in colonoscopy video; this task is as binary classification problem. This method sets a label for each frame as either a negative class (a frame that does not contain polyps) or a positive class (a frame that contains polyps). In order to evaluate the performance of this work, it compares the estimated or predicted tags with the tags annotated by experts. This comparison allows the calculation of the confusion matrix, which includes the following:

- True-positives (TP): the number of frames that the model correctly classifies as positive classes.
- True-negatives (TN): the number of frames that the model correctly classifies as negative classes.
- False-positives (FP): the number of frames incorrectly classified as positive classes by the model.
- False-negatives (FN): the number of frames that the model incorrectly classifies as negative classes.

Using the fuzzy matrix, four classification methods are selected and calculated. These methods evaluate the classification results of the tables with (positive class) and without (negative class) polyp, as well as the overall prediction ability of the two categories:

- Sensitivity measures the proportion of the corresponding classification table containing Po lipids.
- The proportion of lipid containing specificity is not calculated correctly.
- The accuracy shows the prediction ability of me all for polyp image classification.

  Accuracy is the ratio of correctly classified tables, depending on the total number of these tables.

The results obtained are given by each of the deep learning architecture explained in section of methodology. The results of each of the architecture are shown in **Table 3**.

Table 2. Describe the number of sequences and frames selected from each database to evaluate the proposed performance or method*

Data base	Video only		Surface	
	Polyp	Polyp free	Polyp	Polyp free
ASU-Mayo	5	2	2124	2553
CVC-ClinicDB	9	0	191	0
CVC-ColonDB	4	0	145	0
ETIS	7	0	45	0
HU	78	23	21,32	44,460
Total	103	25	23 821	47 013

*This accounts for about 30% of the total number of databases.

Table 3. Results of all proposals*

Metric	InceptionV3	Resnet50	Vgg16
Accuracy	0.81	0.77	0.73
Sensitivity	0.82	0.89	0.81
Specificity	0.81	0.71	0.70
Precision	0.67	0.59	0.56
F1 score	0.74	0.71	0.66
ROC (area under the curve)	0.85	0.87	0.81

*The architecture in the evaluation is specified in the column and each method used is specified in the row.

On the one hand, although most of these architectures show excellent performance in classification tasks, Resnet50 architecture has the best performance because I have well detected positive classes or frames of polyp and obtained a sensitivity of 0.89. On the other hand, the structure of InceptionV3 is the best structure for detecting negative class or frames without polyps, with a specificity of 0.81. In order to evaluate the performance of these architectures in detail, ROC (receiver operating characteristic) curves were constructed by each architecture. In this representation, we try to analyze the model and divide images into specificity and sensitivity by changing the decision threshold according to the probability provided by the model. As shown in **Figure 2**, the Resnet50 architecture can better separate classes without considering the decision threshold. This shows that the architecture can better summarize the variability within and between classes.

10. Conclusion

The detection of adenomatous polyps is the main quality index of colonoscopy, because it is a key index for screening and prevention of CCR. In many countries, the quality of gastrointestinal markers is measured by the amount of these polyps, which can be detected in all colonoscopy examinations. The average rotation of experts is about 25%, but for inexperienced gastrointestinal markers, it may be as low as 10%, which leads to the latter escaping more adenoma.

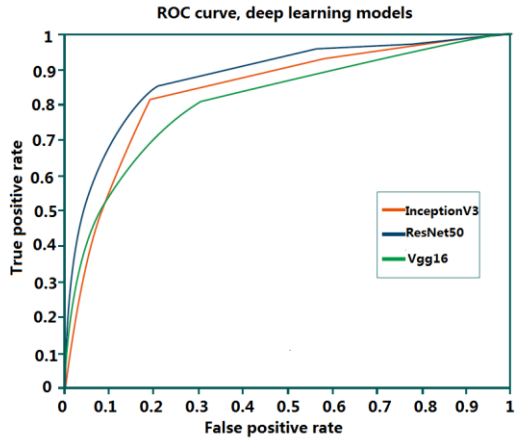

Figure 2. ROC curves for each of the evaluated architectures. The orange line corresponds to the curve of the InceptionV3 architecture; the blue line, to the ResNet50 architecture; and the green line, to Vgg16 architecture. The ResNet50 architecture has better performance, with an area under the curve of 0.87.

This is why some studies[10-12] reported that 26% of polyps were not detected during colonoscopy, which may contribute to more cases of CRC. By 2018, there are 1.8 million new cases worldwide (IARC, 2018)[1]. This is because several factors affect the adequacy of colon scanning, such as the expert's experience and concentration level throughout the working day (related to fatigue), the physiological condition of the colon is a blind spot, and it is difficult to locate the colonoscopy due to the movement of the organ itself and the patient's previous colon preparation, The observability of the colon wall is determined according to the cleanliness of the colon wall[23]. Most of these factors warn that colonoscopy is highly dependent on human factors and requires a second reader unaffected by these factors. In practice, the use of computer tools to detect polyps helps to confirm the findings of experts and, more importantly, remind experts of possible undetected lesions. Therefore, these tools will help to reduce the undetected lipid rate of polyps and thus reduce the incidence of CRC.

In order to support CRC diagnosis using tools of computer vision, this challenge has been solved as follows:

- Detection, referring to the frame-by-frame binary classification of a video into positive class (with polyp) and negative class (without polyp);
- Localization, such as thick delineation (using a box) of the lesion on an image containing polyp;
- Segmentation, as a fine delimitation of the lesion (outlining the edge of the polyp).

The detection of polyps is the primary task facing the whole gastrointestinal tract. The post detection task (localization and segmentation) is a useful process for the expert because he has detected the damage, needs to describe it morphologically, and classifies the graphical user interface as the Paris Classification[6]. This classification enables you to determine the effective management of short-term and long-term diseases. Therefore, these tasks depend entirely on the accuracy of previous detection; therefore, the proposed method completely focuses on the main task required by experts: obtaining colonoscopy images with lesions. In addition, in the prior art, the work of processing these tasks[13-15] describes the limitations when presenting a flow containing at least two tasks. These tasks use different methods for each task, because each task has its own degree of completion. Generally speaking, the polyps frame is detected by measuring the context or global relationship at the image level; the locality and segmentation are analyzed at the pixel level by measuring the local relationship.

In this paper, a robust polyps detection strategy is proposed, which is solved as a classification problem. In the past five years, due to the development of technology, the use of these models has increased to a great extent. These technologies re-

quire a large number of parallel processing and the release of millions of gene databases, such as ImageNet. This makes it possible to design and train highly complex networks, so as to obtain high performance in classification tasks, because it can simulate the high variability of shape, color and texture. However, in the medical field, there is no large amount of public annotation data, so these models are not considered to be applied to disease screening or classification.

The development of transfer learning technology (or transfer learning) provides a solution to solve the shortage of medical data. Use the network weights of millions of natural image training to start a new network and train it with less different data, such as images in colonoscopy. Recent studies using this stream have shown its ability to appropriately summarize the high variability of images with or without polyps lesions in colonoscopy in a specific database. However, different types of lesions and physiological conditions of large intestine are not the only source of variation. The lower the expertise of the specialist, the videos are likely to have a higher number of noisy frames produced by occlusions and abrupt movements of the colonoscopy. In addition, the capture device is also different in light source and visual angle. Therefore, as with existing studies[13-15], training and validation using a database obtained from a specific single gastrointestinal service did not cover all the variability of colonoscopy image classification tasks.

Therefore, in this work, we integrated an attached training video with high variability, which has not appeared in the current technology when collecting security from different databases. This method includes: lesions of different sizes, positions and shapes; colonoscopy and anal surgery by different gastrointestinal experts; and videos taken using different settler reproduction units. Despite this variability, the sensitivity and specificity of detecting polyps in colonoscopy sequence were 0.89 and 0.71.

11. Conclusion

At present, deep learning method is a promising choice, which can be used in classification tasks. With the progress of technology and the continuous design and evaluation of the network, it is possible to integrate a complete set of processes to achieve high performance. Through the evaluation of these networks, the results show that they can be used as the second reader in colonoscopy service.

It is worth noting that these networks fully summarize the high variability of colonoscopy video. The results obtained show that the proposed method can significantly distinguish images regardless of the presence or absence of polyps, regardless of whether the specific clinical protocol of video recording refers to the expert executing the capture program and equipment. This may be an effective method to reduce the detection rate of adenomas for gastrointestinal experts and beginners.

As future work, the proposed method should be tested in a complete colonoscopy procedure and assess whether it is possible to implement it in real time. In addition, a strategy should be developed to not only detect, but also define hazards in the form.

Conflict of interest

The authors declare that they have no conflict of interest.

References

1. Bray F, Ferlay J, Soerjomataram I, et al. Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality for 36 cancers in 185 countries. CA Cancer J Clin 2018; 68(6): 394–424.
2. Data I, Method L. Globocan Colombia 2018. 2018; 380: 1–2.
3. Samadder NJ, Curtin K, Tuohy TM, et al. Characteristics of missed or interval colorectal cancer and patient survival: A population-based study. Gastroenterology 2014; 146(4): 950–960.
4. Katenbach T, Sano Y, Friedland S, et al. American gastroenterological association. American Gastroenterological Association (AGA) institute technology assessment on image-enhanced endoscopy. Gastroenterology 2008; 134(1): 327–340.

5. Brown SR, Baraza W, Din S, et al. Chromoscopy versus conventional endoscopy for the detection of polyps in the colon and rectum. Cochrane Database Syst Rev 2016; 4: CD006439.
6. The Paris Endoscopic Classification of Superficial Tumor Lesions: Esophagus, Stomach and Colon: November 30 to December 1, 2002. Gastrointestinal 2003; 58 (6 supplement): s3-43.
7. Dinerson L, Chua TJ, Kaffees AJ. Meta-analysis of narrowband imaging versus conventional colonoscopy for adenoma detection. Gastrointest Endosc 2012; 75(3): 604–611.
8. Nagorni A, Bjelakovic G, Petrovic B. Narrow band imaging versus conventional white light colonoscopy for the detection of colorectal polyps. Cochrane Database Syst Rev 2012; 1: CD008361.
9. Jin X, Chai S, Shi J, et al. Meta-analysis for evaluating the accuracy of endoscopy with narrow band imaging in detecting colorectal adenomas. Journal of Gastroenterology and Hepatology 2012; 27(5): 882–887.
10. Komenda Y, Suzuki N, Sarah M, et al. Factors associated with failed polyp retrieval at screening colonoscopy. Gastrointest Endosc 2013; 77(3): 395–400.
11. Choi HN, Kim HH, Oh JS, *et al.* Factors influencing the miss rate of polyps in a tandem colonoscopy study. Korean J Gastroenterol 2014; 64(1): 24–30.
12. van Rijn JC, Reitsma JB, Stoker J, et a*l.* Polyp miss rate determined by tandem colonoscopy: A systematic review. Am J Gastroenterol 2006; 101(2): 343–350.
13. Bernal J, Sanchez J, Vilarino F. Towards automatic polyp detection with a polyp appearance model. Pattern Recognition 2012; 45(9): 3166–3182.
14. Younghak S, Balasingham I. Comparison of hand-craft feature based SVM and CNN based deep learning framework for automatic polyp classification. Annu Int Conf IEEE Eng Med Biol Soc 2017; 2017: 3277–3280.
15. Urban G, Tripathi P, Alkayali T, et al. Deep learning Localizes and identifies polyps in real yime with 96% accuracy in screening colonoscopy. Gastroenterology 2018; 155(4): 1069–1078.
16. Taha B, Werghi N, Dias J. Automatic polyp detection in endoscopy videos: A survey. Biomed Eng 2017.
17. Szegedy C, Vanhoucke V, Ioffe S, et al. Rethinking the inception architecture for computer vision. Proc IEEE Comput Soc Conf Comput Vis Pattern Recognit. 2016; 2818–2826.
18. Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. ICLR 2015; 1–14.
19. Zhang X, Zhang X, Li S, et al. Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016. p. 770–778.
20. Tajbakhsh N, Gurudu SR, Liang J. Automated polyp detection in colonoscopy videos using shape and context information. IEEE Trans Med Imaging 2016; 35(2): 630–644.
21. Bernal J, Sanchez FJ, Fernandez-Esparrach G, et al. WM-DOVA maps for accurate polyp highlighting in Colonoscopy: Validation vs. Saliency maps from physicians. Comput Med Imaging Graph 2015; 43: 99–111.
22. Silva J, Histace A, Romain O, et al. Toward embedded detection of polyps in WCE images for early diagnosis of colorectal cancer. Int J Comput Assist Radiol Surg. 2014; 9(2): 283–293.
23. Freedman JS, Harari DY, Bamji ND, et al. The detection of premalignant colon polyps during colonoscopy is stable throughout the workday. Gastrointest Endosc 2011; 73(6): 1197–1206.