Physics in Medicine and Biology

Computer-aided detection of small intestinal ulcer and erosion in wireless capsule endoscopy images

To cite this article before publication: Shanhui Fan *et al* 2018 *Phys. Med. Biol.* in press https://doi.org/10.1088/1361-6560/aad51c

Computer-aided detection of small intestinal ulcer and erosion in wireless capsule endoscopy images

Shanhui Fan[1], Lanmeng Xu[1], Yihong Fan[2], Kaihua Wei[1], Lihua Li[1,3]

[1] College of Life Information Science and Instrument Engineering, Hangzhou Dianzi University, Hangzhou 310018, China

[2] Department of Gastroenterology, Zhejiang Provincial Hospital of Traditional Chinese Medicine, Hangzhou 310006, China

[3] Email: lilh@hdu.edu.cn

Abstract

A novel computer-aided detection method based on deep learning framework was proposed to detect small intestinal ulcer and erosion in wireless capsule endoscopy (WCE) images. To the best of our knowledge, it is the first time that deep learning framework was exploited on automated ulcer and erosion detection in WCE images. Compared with traditional detection method, deep learning framework can produce image features directly from the data and increase recognition accuracy as well as efficiency, especially for big data. The developed method included image cropping and image compression. The AlexNet convolutional neural network (CNN) was trained to the database with tens of thousands of WCE images to differentiate lesion and normal tissue. The results of ulcer and erosion detection reached a high accuracy of 95.16% and 95.34%, a sensitivity of 96.80% and 93.67%, a specificity of 94.79% and 95.98%, correspondingly. The area under the receiver operating characteristic (ROC) curve over 0.98 in both of the networks. The promising results indicate that the proposed method is potential to work in tandem with doctors to detect intestinal ulcer and erosion efficiently.

Keywords: computer-aided detection, ulcer, erosion, convolutional neural network, wireless capsule endoscopy

1. Introduction

Digestive tract diseases, such as esophageal cancer, stomach cancer, and intestine cancer, greatly threaten the human's health with improvement of diet at present. According to "Cancer statistics, 2018", 319,160 new cancer cases and 160,820 cancer deaths in digestive system are projected to occur in the United States (Siegel *et al* 2018). The early detection and treatment will significantly decrease the mortality of digestive tract diseases. The conventional examination methods, including colonoscopy and push gastroscopy, cannot reach the whole small intestine due to its limitation. The invention of wireless capsule endoscopy (WCE) makes up for this deficiency, since it can inspect the whole small intestine without pain, invasiveness, air insufflation and anesthesia (Iddan *et al* 2000). Hence, WCE rapidly become an important and wide-spread diagnostic technique in small intestine diseases and disorders examination (Wang *et al* 2013, Liangpunsakul *et al* 2003).

However, WCE will produce more than 50,000 images during one examination, which will cost two hours on average for an experienced doctor on reviewing all the images (Wang *et al* 2013). The reviewing work is time-consuming, and easily causes false detection and/or missing detection due to oversight of doctors and the limitations of the naked eyes. Therefore, it is of great value to develop a computer-aided lesion detection method to provide support for doctors and further improve accuracy and efficiency of diagnosis.

A new computer-aided detection method was developed to recognize the two main diseases of ulcer and erosion in WCE images in this study. Ulcer and erosion are mucosal lesions in small intestine. Their morbidity is high and will deteriorate to cause death if not treated at early stage. When the lesion is small and superficial, it is erosion (figure 1a). Since the pathological symptoms of erosion are small and unapparent, it is challenged to differentiate from the normal ones. To our knowledge, there are few reports about automatic detection of intestinal erosion. A novel method for automatic erosion detection via deep neural networks was developed in this research.

When the lesion is large and submucosal (i.e. penetrate into muscularis mucosa), it is regarded as ulcer (figure 1b). Ulcer has various pathological characteristics, such as erodes blood vessel, which appears as hole, and causes small intestinal stenosis, which make it difficult to be detected precisely. Several efforts have been made to achieve automatic ulcer detection in WCE images (Li and Meng 2009a, Yeh *et al* 2014, Li *et al* 2009, Li and Meng 2009b, Karargyris and Bourbakis 2011, Chen and Lee 2012, Yu *et al* 2012, Kundu *et al* 2016). These research works can be roughly divided into two parts according to the feature patterns extracted for classification. One is to use color feature of WCE images to realize ulcer automatic detection (Li and Meng 2009a, Yeh *et al* 2014), because the dominant color of ulcer is obvious, which appears to be yellowish or whitish, unless it is covered with blood or clots. The other one is to use texture feature of WCE images (Li *et al* 2009, Li and Meng 2009b, Karargyris and Bourbakis 2011, Chen and Lee 2012, Yu *et al* 2012, Kundu *et al* 2016), such as Li *et al.* (Li and Meng 2009b) presented a method of combining curvelet transformation and local binary pattern (LBP) to extract the texture feature, and then multilayer perceptron (MLP) neural network and support vector machines (SVM) classifier was used to recognize ulcer images, Karargyris *et al.* (Karargyris and Bourbakis 2011) utilized log Gabor filters and textural descriptors to differentiate the normal and ulcer region, and Yu *et al.* (Yu *et al* 2012) proposed a detection method via LBP, scale-invariant feature transform (SIFT) operators and feature fusion technique. However, all of reported ulcer detection methods (Kundu *et al* 2016, Yu *et al* 2012, Chen and Lee 2012, Karargyris and Bourbakis 2011, Li and Meng 2009b, Yeh *et al* 2014, Li *et al* 2009, Li and Meng 2009a) used manual feature extraction and traditional machine learning methods, which had several drawbacks, such as the inability to extract recessive feature of the image, poor robustness and applicability.

Figure 1. Illustration of erosion (a), ulcer (b) and normal (c) WCE images

Therefore, an improved method based on convolutional neural network (CNN), one of the most common deep learning frameworks, was developed in this study. Compared with traditional image recognition methods, CNN replaces manual feature extraction with computerized feature learning, so it can find more feature patterns that handcrafted features failed to describe. Moreover, CNN is an end-to-end learning system combing features extraction and classification together, which is easier to tune the model to reach optimal performance. The advantages of CNN will significantly improve its recognition accuracy as well as efficiency. It has shown great superiority in various image recognition tasks (Krizhevsky *et al* 2012, Kim 2014, Shin *et al* 2016), such as bleeding detection in fundus images (van Grinsven *et al* 2016) or WCE images (Jia and Meng 2016, Jia and Meng 2017, Li *et al* 2017).

In this study, we proposed to explore CNN on small intestinal ulcer and erosion detection. To the best of our knowledge, it is the first time that CNN was exploited for ulcer and erosion detection in WCE images. The rest of this paper was organized as below. Section 2 described the detection method for small intestinal ulcer and erosion in detail. Section 3 presented the experimental results. Section 4 discussed the results. Finally, Section 5 concluded the significance of the study and discussed the outlook of the future research.

2. Methods

2.1 Dataset and Preprocessing

The dataset used were selected from 144 patients, including 32 cases of erosion, 47 cases of ulcer, and 65 normal cases. We trained two independent models for lesions detection, one was for ulcer detection, and the other was for erosion detection. The dataset used in ulcer detection contained 3,250 ulcer images and 5,000 normal images. And the dataset used in erosion detection was consisted of 4,910 erosion images and 8,000 normal images. The dataset will be divided into three parts randomly for training and evaluating detection model on image level. The training set and testing set was used for model training, while verification set was used for evaluating the performance of the trained model. There was no overlap in these three datasets. The data distribution for the two lesions detection was shown on table 1 and 2.

Table 1. The data distribution for ulcer detection method

	Training set	**Testing set**	**Verification set**	**Total**
Ulcer	2000	500	750	3250
Normal	2400	600	2000	5000

Table 2. The data distribution for erosion detection method

	Training set	**Testing set**	**Verification set**	**Total**
Erosion	2720	690	1500	4910
Normal	3200	800	4000	8000

As shown in figure 2a and c, the initial WCE images contained black margin and data and time of image acquisition around the tissue without any useful information for recognition. So before training and testing, a mask technique was used to crop the black margin to speed up the training and testing. The images after cropping are shown in figure 2b and d, and their images size is 511×511.

(a) Original WCE image with erosion (b) Preprocessed WCE image with erosion (c) Original WCE image with ulcer (d) Preprocessed WCE image with ulcer

Figure 2. The original and preprocessed WCE images with erosion or ulcer

2.2 CNN architectures

In this work, we explored AlexNet, one of the most classic CNN architectures, to detect the abnormal regions (ulcer or erosion) based on a tradeoff between time cost and model capability. AlexNet was proposed by Alex Krizhevsky in 2012 (Krizhevsky *et al* 2012). As shown in figure 3, AlexNet contains eight learning layers with weights: the first five layers are convolutional and the remaining are fully-connected. Each learning layer works with rectified linear units (RELU). Additionally, the first, second, and fifth convolutional layers are followed by max-pooling layer, the first two fully-connected layers are followed by dropout layers. The dropout technique is used to reduce overfitting. The last fully-connected layer is followed by a 1000-way softmax. The 1000-way softmax in original AlexNet was modified into 2-way output to indicate the normal and abnormal probability of the input image in this work. The threshold to tell normal and abnormal apart was 0.5. The input of AlexNet is with a fixed size of 227× 227 pixels, so the cropped WCE image need to be compressed appropriately before training. The details about AlexNet architecture can be seen in (Krizhevsky *et al* 2012).

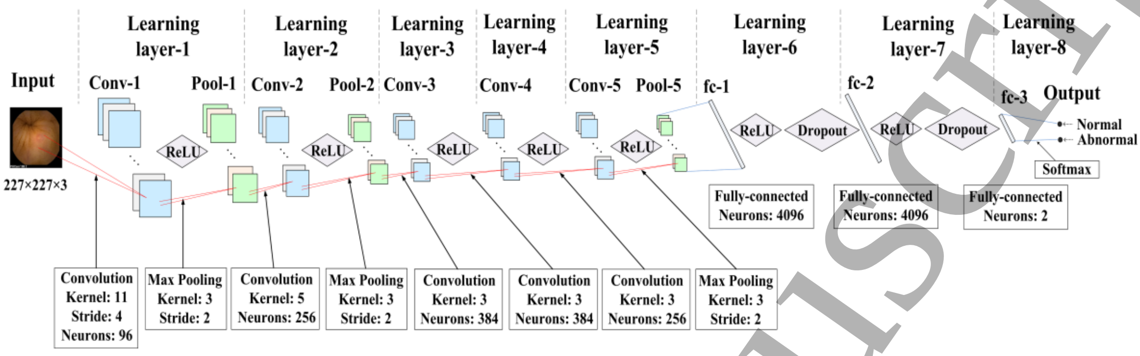

Figure 3. Illustration of our proposed CNN architecture

2.3 CNN Training

Both of the two detection models were trained by using stochastic gradient descent method with a batch size of 50, initial learning rate of 0.01, momentum of 0.9, and weight decay of 0.001, separately. The initial weight was derived from a zero-mean Gaussian distribution with standard deviation 0.01. The update rule for weight w was as follows (Krizhevsky *et al* 2012):

$$\begin{cases} v_{i+1} = 0.9 \cdot v_i - 0.001 \cdot \varepsilon \cdot w_i - \varepsilon \cdot \left\langle \frac{\partial L}{\partial w} \Big|_{wi} \right\rangle_{D_i} \\ w_{i+1} = w_i + v_{i+1} \end{cases} \tag{1}$$

where i was the iteration index, v was the momentum variable, ε was the learning rate, and $\left\langle \frac{\partial L}{\partial w} \Big|_{wi} \right\rangle_{D_i}$ was the average over the ith batch D_i of the derivative of the objective with respect of *w*, evaluated at w_i.

The learning policy of "step" was chose for the training. The learning rate will be changed by a certain number of iterations which was set by the value of stepsize. With one change, the learning rate will drop by multiplying 0.1. Thus, the total times of learning rate changed is determined by stepsize and maximum iterations, which is crucial for the accuracy of training results. The maximum iterations for ulcer and erosion detection were set to 2,200 and 6,000, respectively. The parameter of stepsize was set to adjustable to find an optimal model, which means the times of learning rate changed varied correspondingly.

The CNN training was performed with the Caffe framework (Jia *et al* 2014) on a NVIDIA GK104GL GPU.

2.4 Performance Measures

The accuracy, sensitivity and specificity were calculated to evaluate the recognition performance of the trained CNN model. The definitions of these indices were as follows:

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{2}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

where TN (True-Negative) was the number of correct predicted normal images, TP (True-Positive) was the number of correct predicted abnormal images, FN (False-Negative) was the number of predicted normal images that are actually abnormal, FP (False-Positive) was the number of predicted abnormal images that are actually normal.

In addition, the receiver operating characteristic (ROC) curve and area under ROC curve (AUC) was performed to further evaluate the accuracy and reproducibility of lesion recognition (Bradley 1997).

3. Results

3.1 Performance of training model

The AlexNet architecture was fine-tuned on the training to get optimal performance. We performed 20 independent experiments with the change of the times of learning rate changed to find a model with highest accuracy for both ulcer and erosion detection. The times of learning rate changed was ranged from 1 to 20. Figure 4 shows that when the learning rate changed six times, the accuracy of training model for both ulcer and erosion detection was highest, which was 96.36% and 94.68%, respectively. At this point, the stepsize was 367 and 1,000 for ulcer and erosion model, respectively, and the final learning rate was 10^{-8} for both ulcer and erosion trained model. The trained models with highest accuracy will be further evaluated in verification test.

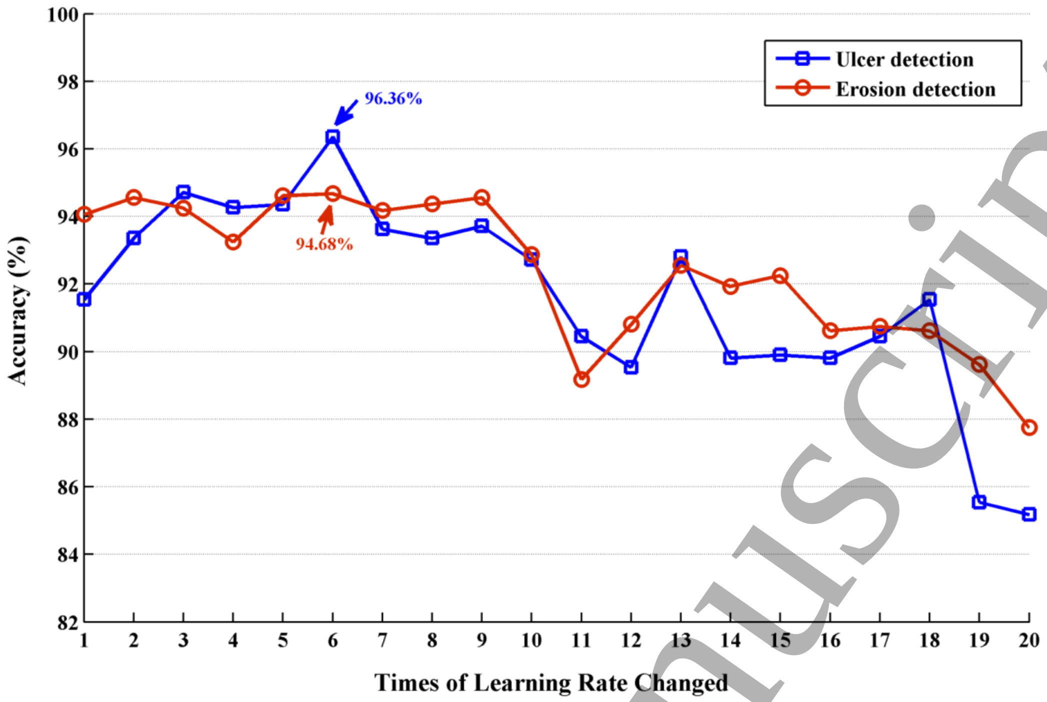

Figure 4. The change of training accuracy with varied times of learning rate changed

Figure 5 shows the feature maps extracted from the first convolution layers of the two AlexNet models for ulcer and erosion detection. The patterns of different intestinal positions and/or different lesions were different in their feature maps. For example, for lesion image, it contained some color information which normal image didn't contain. The kernels in the convolutional layers were initialized randomly before training, various kinds of features can be learned directly from images including higher-level feature that hardly extracted by handcrafted extraction methods. Hence, features extracted by CNN architecture were more effective, which will be greatly benefited to lesion detection of WCE images.

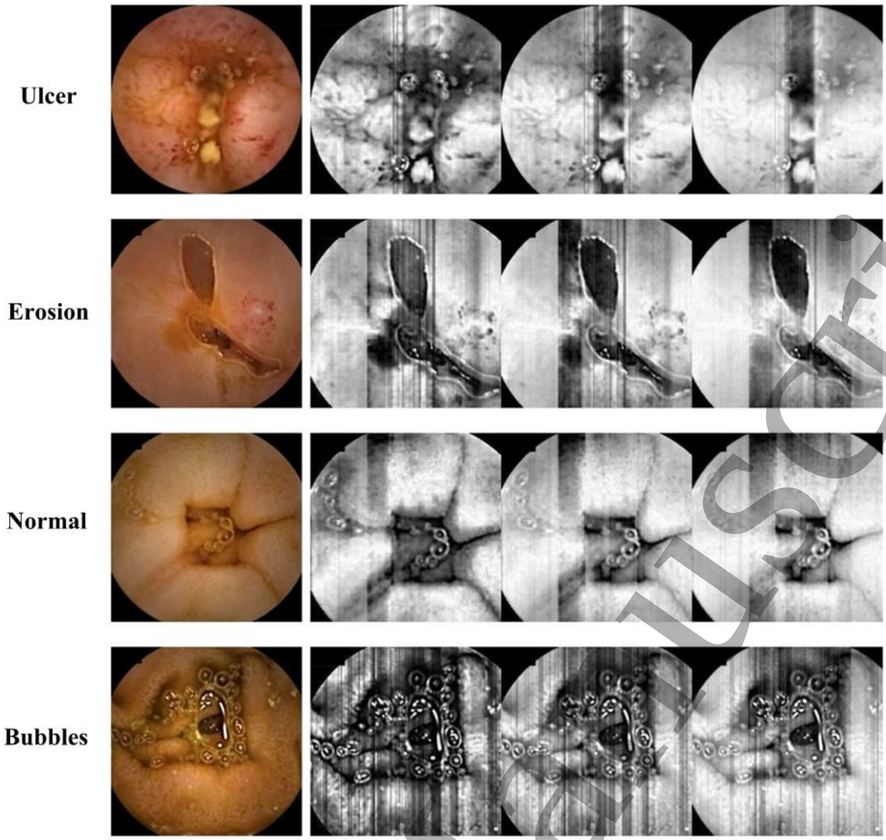

Figure 5. Feature maps from the first convolutional layer

3.2 Evaluation of trained CNN models on lesions recognition

Verification test was performed to evaluate the reliability and practicability of the trained model. In order to evaluate the performance of trained model objectively as far as possible, the verification procedure was performed with five different verification subsets. The images in verification set were unlabeled. The images of verification set were input into the trained model, and to be classified into abnormal or normal one by one. The results of the classification were judged by an experienced doctor. Finally, the accuracy, sensitivity, and specificity were calculated.

The verification set of ulcer detection were randomly divided into five subsets on average (i.e., 150 ulcer and 400 normal images per verification set). There was no overlap among five subsets. As shown in table 3, the averaged accuracy, sensitivity and specificity of verification part are 95.16%, 96.80%, and 94.79%, respectively, which corresponding to a missing detecting rate of 3.20% and false detecting rate of 5.21%.

Table 3. Performance of the auto-detection model of ulcer with five different verification subsets

	1	**2**	**3**	**4**	**5**	**Average**
Accuracy	94.91%	94.55%	96.18%	94.73%	95.45%	95.16%
Sensitivity	94.00%	98.67%	97.33%	97.33%	96.67%	96.80%
Specificity	95.49%	93.00%	95.75%	94.22%	95.48%	94.79%

The verification set of erosion detection were randomly divided into five parts on average (i.e., 300 erosion and 800 normal images per verification set) as well. There was no overlap among five subsets. As shown in table 4, the averaged accuracy, sensitivity and specificity of verification part are 95.34%, 93.67%, and 95.98%, respectively, which corresponding to a missing detecting rate of 6.33% and false detecting rate of 4.02%.

Table 4. Performance of the auto-detection model of erosion with five different verification subsets

	1	**2**	**3**	**4**	**5**	**Average**
Accuracy	94.63%	95.45%	95.64%	95.36%	95.64%	95.34%
Sensitivity	92.00%	92.67%	94.33%	94.67%	94.67%	93.67%
Specificity	95.63%	96.50%	96.13%	95.63%	96.00%	95.98%

Furthermore, the ROC curves were drawn to evaluate the robustness and veracity of the two best-trained models, as well as the AUC value. As shown in figure 6 and 7, all of ROC curves are much closed to the upper left corner of the axis, and the averaged AUC value for ulcer and erosion detection model is 0.9891 and 0.9863, respectively. Both of them proved that the models have high reproducibility and accuracy for lesion detection.

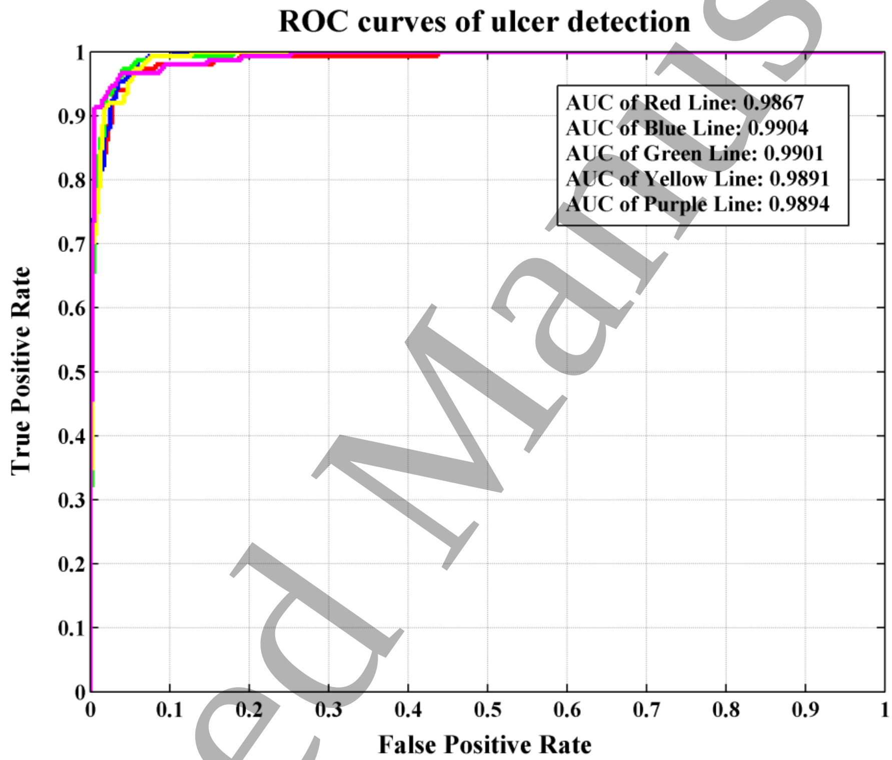

Figure 6. The ROC curves and AUC values for ulcer detection with five verification subsets. Each colored line represented the result of one verification procedure

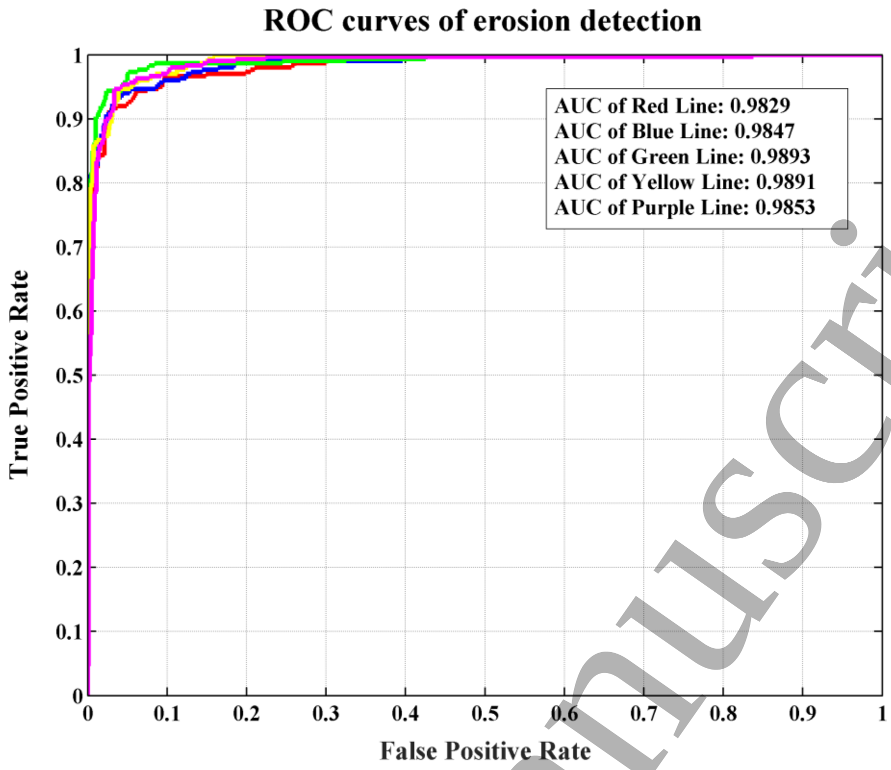

Figure 7. The ROC curves and AUC values for erosion detection with five verification subsets. Each colored line represented the result of one verification procedure

To further demonstrate performances of the proposed method, we compared it with the approach that combined gray scale histogram and SVM classifier which was similar with that reported by (Kundu *et al* 2016). This method was implemented on the same training and verification sets as those used in our AlexNet approach to perform a direct comparison. The results of the classification were judged by the same experienced doctor. The results are shown in table 5 and 6. The sensitivity, specificity, accuracy and AUC in tables were the average of those tested with five verification subsets. The comparative results illustrated that our proposed method leads to an increase for all four metrics.

Table 5. Performance comparison between traditional recognition method and CNN on ulcer detection

Method	Sensitivity	Specificity	Accuracy	AUC *
Histogram-SVM	52.53%	77.50%	70.69%	0.6153
Proposed method	96.80%	94.79%	95.16%	0.9891

***:** area under the receiver operating characteristic (ROC) curve

Table 6. Performance comparison between traditional recognition method and CNN on erosion detection

Method	Sensitivity	Specificity	Accuracy	AUC *
Histogram-SVM	38.93%	79.10%	68.14%	0.6273
Proposed method	93.67%	95.98%	95.34%	0.9863

***:** area under the receiver operating characteristic (ROC) curve

4. Discussion

In this study, three types of databases (normal, ulcer and erosion) were used for developing a computer-aided detection method for small intestinal ulcer or erosion. This method was actualized by implementing CNN architecture that has been explained in the previous sections. The experimental results confirmed that the proposed method has high accuracy, sensitivity and specificity on both ulcer and erosion recognition. Comparing performance of the two lesion detection models, the sensitivity of ulcer detection was much higher than that of erosion detection (table 3 and 4). The main reason is that the pathological symptoms of ulcer are more obvious than those of erosion. Ulcer is usually in the form of block and attaches white and/or yellow fur, while erosion is small and punctiform (figure 1a and b). Therefore, the features of ulcer in WCE images can be learned better, which leads to a higher sensitivity in ulcer detection. The performance of ROC curves and AUC values (figure 6 and 7) also confirmed that it was more difficult to differentiate the erosion from normal tissue.

This is first time to explore automatic detection method on small intestinal erosion, which will be a huge step for erosion examination in clinic. Although several methods were applied to recognize ulcer, all of them used manual feature extraction and traditional machine learning methods (Li and Meng 2009a, Yeh *et al* 2014, Li *et al* 2009, Li and Meng 2009b, Karargyris and Bourbakis 2011, Chen and Lee 2012, Yu *et al* 2012, Kundu *et al* 2016). These methods were time-consuming, complex and difficult to design and tune the overall performance of model to get a satisfactory result because many image processing steps needed to be considered at the same time. Our approach was different from the previous studies. It was based on deep learning framework. The deep learning model is an end-to-end system, which avoids the complex design of feature extraction and classification framework. Moreover, it is able to produce features directly from the image. Both of them greatly benefit to increase recognition accuracy as well as efficiency, especially for big data. Utilizing these advantages, the proposed approach obtained predictive results, which were better than most of previous studies

(Li and Meng 2009a, Yeh *et al* 2014, Li *et al* 2009, Li and Meng 2009b, Karargyris and Bourbakis 2011, Yu *et al* 2012, Kundu *et al* 2016). The results reported by Chen *et al.* (Chen and Lee 2012) was a bit better than ours, whose accuracy, sensitivity and specificity on ulcer recognition can reach up to 96.32%, 91.67% and 99.39%, but they only used a few hundred WCE images for training and testing. The comparative results shown in table 5 and 6 further confirmed the superiority of the proposed method based on CNN.

Since the dataset used for training and verification was split on image level rather than patient level due to the limitation of case load, it may lead to positive bias on detection results. Hence, five verification procedures were performed with different verification subsets to minimize the influence caused by the inter-relation of images from the same person, which ensured that the evaluation of performance of the trained model was objective as far as possible. Furthermore, three new cases of erosion and four new cases of ulcer were added to further verify performance of the two trained models, which means the images in this verification part were independent with those used for model training. The results still showed high performance for both ulcer and erosion detection with a sensitivity of 91.35% and 93.33%, a specificity of 95.83% and 96.61%, an accuracy of 95.43% and 96.32%, an AUC value of 0.9805 and 0.9904, correspondingly. Although only a few new cases were used for this verification, it still proved the feasibility, reproducibility and practicability of using the proposed method to automatically detect ulcer and erosion in WCE images.

Although the proposed method showed an excellent performance in detecting ulcer and erosion, it still failed to recognize some ulcer, erosion and normal WCE images. Figure 8 shows some typical misclassification images. In figure 8, the first row are ulcer images which are misclassified as normal images, the second row are normal images which are misclassified as ulcer images, the third row are erosion images which are misclassified as normal images, and the last row are normal images which are misclassified as erosion images. An empirical analysis was done for these misclassified images. The main factors caused the misclassification are concluded as follows: (1) The symptom of ulcer or erosion is subtle, which is almost the same with the normal tissue, leading to be difficult to recognize (figure 8a-c, f-h); (2) The bubbles in small intestine will be the distractions in image recognition; (3) Some normal WCE images containing blood vessels (figure 8e and k) or yellow impurities (figure 8d and j), will be easily recognized into abnormal image due to the similar color feature; (4) Some images containing intestinal villus were easily attached by impurities, leading to misclassification into abnormal (figure 8i); (5) Poor image quality also will affect the accuracy of recognition, such as over or under exposure (figure 8g), or out of focus (figure 8h). The analysis for misclassification will be performed emphatically in the follow-up work, to find a way to further increase the accuracy of lesion detection.

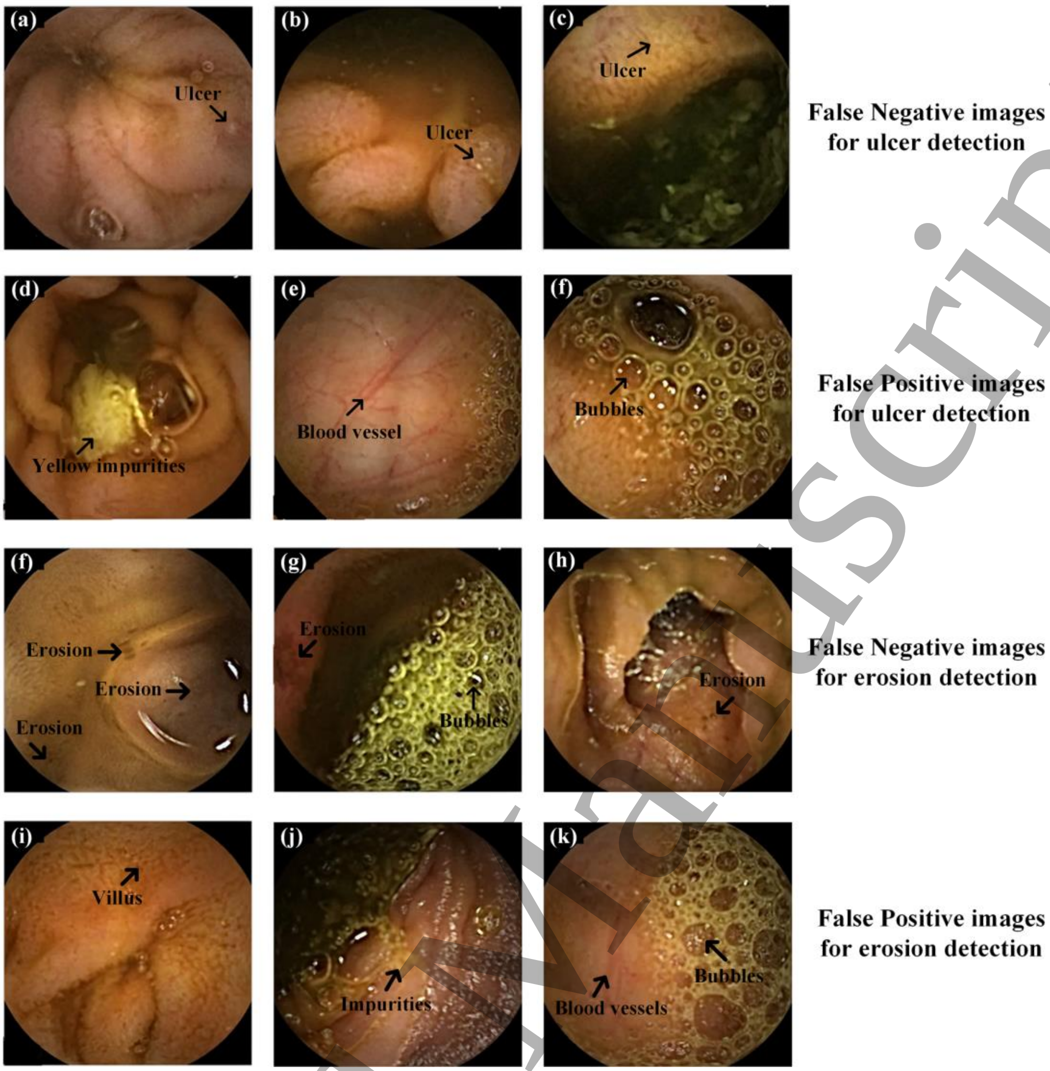

Figure 8. The misclassified images in ulcer or erosion detection

5. Conclusions

A new computer-aided approach based on CNN was proposed to precisely detect small intestinal ulcer and erosion in WCE images. To the best of our knowledge, this is the first time that deep learning framework was applied in ulcer and erosion detection. Experimental results showed superior performance on ulcer and erosion detection with an accuracy of 95.16% and 95.34%, a sensitivity of 96.80% and 93.67%, a specificity of

94.79% and 95.98%, correspondingly.

The comparisons between the performances of the proposed method and traditional recognition method combining gray scale histogram and SVM classifier also demonstrated that features learned by CNN outperformed the latter in lesions detection, even for relatively small number of training images. Moreover, according to the advantages of deep learning, the more data the better results can be obtained. The promising performance indicates that the proposed method is enormously potential to be applied in clinic, which will greatly relieve the heavy reviewing burden of doctors.

Although excellent performance has been achieved, there were still about 5% of WCE images cannot be detected correctly. To further improve the accuracy of the CNN method in detecting ulcer and erosion, in next work, besides finding solutions for misclassification and applying deeper CNN networks (e.g., VGGNet, GoogleNet and so on), the database also will be augmented to achieve more features of lesions. Furthermore, in order to further increase the practicability on computer-aided diagnosis, a new method for multiple recognition of different lesions (e.g., bleeding, ulcer, erosion, polyp, tumor and so on) in digestive tract will be designed, since the detection of multiple lesions in WCE is more significant and needed in clinic, and yet the present methods are just for single lesion detection.

Acknowledgement

This work was supported by National Natural Science Foundation of China (Grant number 81601530) and the Science and Technology Project of Zhejiang Province of China (Grant number 2017C33143). The authors have no conflicts of interest to disclose.

References

Bradley A P 1997 The use of the area under the ROC curve in the evaluation of machine learning algorithms *Pattern Recogn.* **30** 1145-59

Chen Y and Lee J 2012 Ulcer detection in wireless capsule endoscopy video *Proc. 20th ACM Int. Conf. Multimed.* pp 1181-4

Iddan G, Meron G, Glukhovsky A and Swain P 2000 Wireless capsule endoscopy *Nature* **405** 417

Jia X and Meng M Q-H 2016 A deep convolutional neural network for bleeding detection in Wireless Capsule Endoscopy images *Proc. 38th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* pp 639-42

Jia X and Meng M Q-H 2017 Gastrointestinal bleeding detection in wireless capsule endoscopy images using handcrafted and CNN features *Proc. 39th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* pp 3154-7

Jia Y, Shelhamer E, Donahue J, Karayev S, Long J, Girshick R, Guadarrama S and Darrell T 2014 Caffe: Convolutional architecture for fast feature embedding *Proc. 22nd ACM Int. Conf. Multimed.* pp 675-8

Karargyris A and Bourbakis N 2011 Detection of small bowel polyps and ulcers in wireless capsule endoscopy videos *IEEE T. Biomed. Eng.* **58** 2777-86

Kim Y 2014 Convolutional neural networks for sentence classification *Proc. 2014 Conf. Empir. Methods Natl.Lang. Process.* pp 1746-51

Krizhevsky A, Sutskever I and Hinton G E 2012 Imagenet classification with deep convolutional neural networks *Proc. Adv. Neural Inf. Process. Syst.* pp 1097-105

Kundu A, Bhattacharjee A, Fattah S and Shahnaz C 2016 Automatic ulcer detection scheme using gray scale histogram from wireless capsule endoscopy *Proc. 2016 IEEE Int. WIE Conf. Electr. Comput. Eng.* pp 242-5

Li B and Meng M Q-H 2009a Computer-based detection of bleeding and ulcer in wireless capsule endoscopy images by chromaticity moments *Comput. Bio. Med.* **39** 141-7

Li B and Meng M Q-H 2009b Texture analysis for ulcer detection in capsule endoscopy images *Image Vision Comput.* **27** 1336-42

Li B, Qi L, Meng M Q-H and Fan Y 2009 Using ensemble classifier for small bowel ulcer detection in wireless capsule endoscopy images *Proc. Int. Conf. IEEE Robot. Biomim.* pp 2326-31

Li P, Li Z, Gao F, Wan L and Yu J 2017 Convolutional neural networks for intestinal hemorrhage detection in wireless capsule endoscopy images *Proc. 2017 IEEE Int. Conf. Multimed. Expo* pp 1518-23

Liangpunsakul S, Chadalawada V, Rex D K, Maglinte D and Lappas J 2003 Wireless capsule endoscopy detects small bowel ulcers in patients with normal results from state of the art enteroclysis *Am. J Gastroenterol.* **98** 1295-8

Shin H-C, Roth H R, Gao M, Lu L, Xu Z, Nogues I, Yao J, Mollura D and Summers R M 2016 Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning *IEEE T. Med. Imaging* **35** 1285-98

Siegel R L, Miller K D, and Jemal A 2018 Cancer statistics *CA Cancer J. Clin.* **68** 7-30

van Grinsven M J, van Ginneken B, Hoyng C B, Theelen T and Sánchez C I 2016 Fast convolutional neural network training using selective data sampling: Application to hemorrhage detection in color fundus images *IEEE T. Med. Imaging* **35** 1273-84

Wang A, Banerjee S, Barth B A, Bhat Y M, Chauhan S, Gottlieb K T, Konda V, Maple J T, Murad F and Pfau P R 2013 Wireless capsule endoscopy *Gastrointest. Endosc.* **78** 805-15

Yeh J-Y, Wu T-H and Tsai W-J 2014 Bleeding and ulcer detection using wireless capsule endoscopy images *J. Softw. Eng. Appl.* **7** 422-32

Yu L, Yuen P C and Lai J 2012 Ulcer detection in wireless capsule endoscopy images *Proc. 21st Int. Conf. IEEE Pattern Recognit.* pp 45-8