Human Stools Classification for Gastrointestinal Health based on an Improved ResNet18 Model with Dual Attention Mechanism

Jing Zhang, Tao Wen, Tao He, Xiangzhou Wang, Ruqian Hao, Juanxiu Liu, Xiaohui Du* , Lin Liu
University of Electronic Science and Technology of China, MOEMIL Laboratory

Abstract

The human stools are directly related to the health of human gastrointestinal function. Preliminary classification of the shape and colour of stools can diagnose the health status of peoples, therefore automatic recognition of stools is the current development direction of smart toilets. Due to the difficulty in identification with complex image content, this paper proposed a convolutional neural network called StoolNet to solve the current challenges. The architecture of StoolNet is based on ResNet and contains two output branches which perform colour and shape recognition, respectively. To improve the recognition performance, the dual attention mechanism was introduced into feature extraction stage. The accuracy value of our proposed model could achieve 99.7% and 94.4% for color and shape recognition on our test set, respectively. Experimental results show that, compared with other stool classification algorithms, our method possesses better capability of category discrimination on real dataset.

1. Introduction

When human gastrointestinal tract is diseased, there will be a series of symptoms, such as pain, nausea, vomiting, diarrhea, loss of appetite, etc. Gastrointestinal diseases can cause death in severe cases, if no preventive actions are taken and no early detection is used. Human gastrointestinal lesions are quite common and mainly divided into three stages: gastric precancerous disease, early gastric cancer and advanced gastric cancer. Lesions can rarely be cured when patients with advanced gastric cancer [21]. However, when the gastrointestinal lesion is detected in the early stage, there is a greater chance of being cured. The stools are directly related to the health of human gastrointestinal function. Consequently, if patients can find abnormalities in the stools when their gastrointestinal tract is diseased, they can seek medical advice as soon as possible before the condition worsens.

Stool detection methods include two major aspects, subjective – the observation of the shape, consistency and colour of the stool [3, 6, 7] and objective – microscopic detection and chemical analysis. However, the microscopic and chemical testing of stools requires experiment by professional physicians in a laboratory. Obviously, these objective methods are inaccessibly used in daily stool states monitoring for individuals, because there is an imbalance between the supply and demand for medical services which has caused conflicts in the patient-doctor relationship. For the subjective method to classify the stool shape or evaluate the stool consistency, the Bristol Stool Form Scale (BSFS) is a clinically validated classification scale and is widely used in clinical practice [2]. The BSFS defines seven categories based on the consistency of stools. As shown in Fig. 1, types 3 and 4 are considered to be normal categories, while types 1 and 2 are constipation. Type 5 is considered to denote mild diarrhoea due to a lack of fibre and no clear edges, while types 6 and 7 are moderate and severe diarrhoea, respectively. The colour of normal adult stool is yellow, golden, or yellowish brown, while black, bright red, dark red, grey white and green are regarded as abnormal colours [6]. Although the subjective methods do not require professional equipment and laboratory, the observers still need relevant professional knowledge, which is apparently unrealistic for individuals.

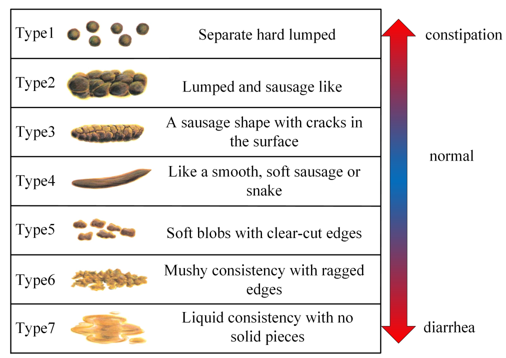


Figure 1. Bristol Stool form scale [2].

It has become a trend that patients provide doctors with personal data, which is collected by themselves with quantified-self, self-monitoring or life-logging movements

[4, 5, 11]. A practicable way is that individuals use smartphone to shoot stool images and send them to doctors. But a large number of stool images from different people is a heavy workload for doctors. The data recorded by patients are non-standardised due to a lack of professional training or learning, which limits the precision and objectivity of self-reports. Moreover, it is a difficult and arduous task for patients to conduct self-tracking experiments.

With the development of computer hardware and software technologies in recent years, machine learning methods represented by deep learning have been widely used in various fields. Many achievements have been made in the field of medical services, and deep learning systems can help doctors to diagnose diseases. Deep learning can automatically classify medical images or automatically detect specific targets to give a second opinion independent of the doctor [13, 15]. Therefore, automatic photo taking and recognition of stools is the current development direction of smart toilets [8, 14].

The result of color recognition will be disturbed by the urine in the toilet. In addition, loose stools are distributed throughout the toilet with no solid pieces and some pictures contain stools of various shapes. Due to the difficulty in identification with complex image content, this paper proposes a convolutional neural network (CNN) called StoolNet to solve the current challenges. We mainly propose a computer vision-based method to automatically classify and recognize the shape and colour of human stool to replace artificial, reduce the burden on users, and provide doctors with more accurate results of automatic stool detection; this will lead to people receiving better medical and health services. In the work of this article, our primary contributions are as follows:

1) We built a new human stool image dataset, which was collected by volunteers and labelled by professional doctors.

2) We proposed a CNN model called StoolNet which architecture is based on ResNet18 and contains dual attention mechanism in feature extraction stage. The two output branches shared partial convolution structure for the multi-task classification of the shape and colour stool samples.

3) Our research of the four-type classification of stool shape is more complete than previous studies on three-type classification. In addition, we have implemented a two-type classification of stool colour, which has not been studied in previous researches.

4) Our detection results on real samples are better than previous related studies. The accuracy of stool shape recognition and colour classification reaches 94.4% and 99.8 %, respectively.

2. Related work

As computational power has increased and the cost of hardware has decreased, deep learning method has the advantages of fast computing speed and high accuracy. Therefore, in recent years, researchers have begun to adopt deep learning methods in the field of stool detection. Seung-min Park [14] have developed a smart toilet system to realise personalised health detection by analysing human excrement. The system automatically classifies stool samples based on BSFS and deep learning methods of inception CNN. In this study, the dataset were labelled by two professional doctors according to BSFS. Finally, the performance of this system is compared with the classification results of 5 medical students, and the standard area under the curve (AUC) evaluation metric is used. Although the results show that the classification results of CNN are slightly better than those of medical students, the paper did not elaborate on the recognition technology of stools, and did not give specific details when training the CNN network. For example, the introduction of the training set and the test set, the accuracy of each category, and the model parameter settings, etc. They only gave the AUC of the three categories of stool, making it difficult to prove that their model can work well in actual situations.

Hachuel *et al*. [8] also proposed a deep learning method that combines segmentation and recognition to automatically classify stools. In this research, the SegNet [1] was introduced to detect the stool area in the original image to eliminate any background and metric value of mean intersection over union reached 71.93%. Then the segmented target area was inputted into ResNet18 for classification and the classification accuracy of this method reached 74.62%. The dataset were annotated to three categories(normal, constipation, and diarrhea) by professional doctors according to the BSFS table. They believed that as the data set increases, the accuracy of the model will be further improved, so 25,200 stool images were made using play-doh. After retraining the network, an accuracy of 99.4% was achieved on the test set of 10,800 images. Their problem is that all samples from the test set of real samples were identified as "normal". And they used non-real samples, which will cause the results of the CNN model to predict inconsistencies with the labels of the real samples, so they could not be used in practice.

Although some CNN-based stool classification researches have been proposed, these methods still have shortcomings and cannot be used in real-life situations. Therefore, in this study, we presented an end-to-end framework, called StoolNet, for automatic recognition of stool shape and colour. Our work not only improves the recognition of stool shape and completes the four classification tasks, but also discusses the recognition of stool colour which is seldom studied before.

3. Method

Given an image of stool, the goal of our model is to automatically recognize the shape and colour of this stool image. The key idea of our method is using one end-to-end network to complete the shape and colour classification task at the same time. Backbone of ResNet18 [9] was chose to be the feature extractor which is shared by the two tasks, so that weights of convolutional layers could not be double-calculated. Two output branches which contain fully connected layers are used as classification head of shape and colour and connected to the last feature map. In order to improve the recognition performance, a dual attention block was added behind the feature extractor.

3.1. Network structure

Figure 2 depicts the StoolNet structure. This structure can be divided into two parts: one is a fully convolutional network architecture including all convolution layers, and it is regarded as the feature extractor. The other is the classifier part, which is composed of two classification heads for colour and shape.

The Backbone of ResNet18 [9] was used as the feature extractor which include one convolutional layer with a 7×7 kernel, two basic block A and six basic block B. The two types of basic blocks used in Fig. 2 are shown in Fig. 3. The additional dual attention block used in Fig. 2 was inspired by Deep Convolutional Networks [16], as shown in Fig. 4.

The dual attention module contains position and channel attention modules, which can make it possible for the network to learn 'what' and 'where' to attend in the channel and spatial axes respectively. The purpose of introducing Position Attention Module (PAM) is to capture the rich contextual information between pixels and encode the contextual information into local features to enhance their representation capability. The input feature map with a shape of $C \times H \times W$ followed by a convolution layers to produce three feature maps B1, C1 and D1. Then B1 and C1 are reshaped to $C \times N$, where $N = H \times W$. The matrix multiplication result between the transpose of C1 and B1 is followed by a softmax layer to calculate the spatial attention map. The Channel Attention Module (CAM) was introduced to establish the interdependence between different channels, and improve the feature representation of specific semantics. Different from PAM, the input feature map is directly reshaped to produce B2 and C2 with the shape of $C \times N$, and then apply a matrix multiplication between input and D2 (the transpose of input with the shape of $C \times N$). Same with PAM, a softmax layer is applied to calculate the channel attention map. As shown in Fig. 2, after fusing PAM and CAM, dual attention layer is followed by the two classification head of colour and shape.

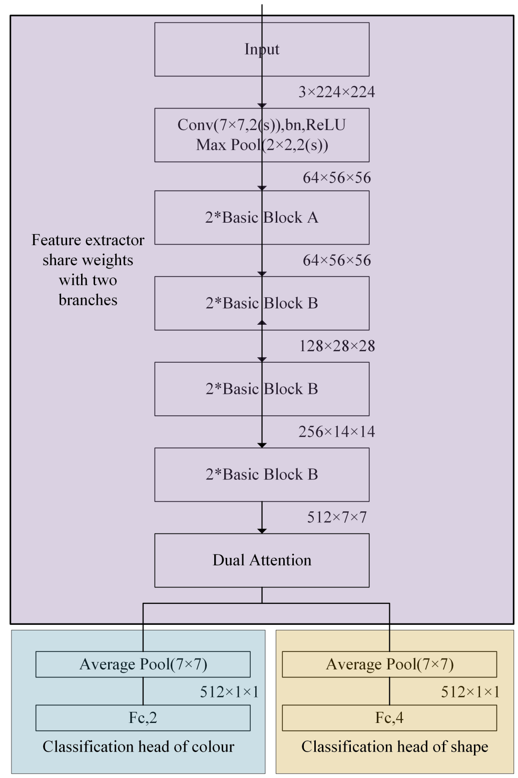


Figure 2. Bristol Architecture of StoolNet.

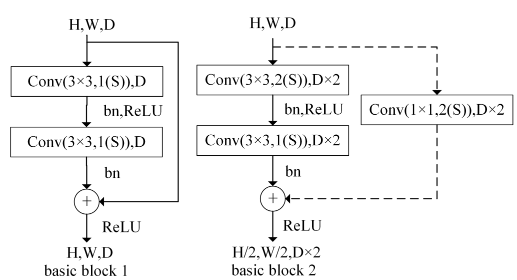


Figure 3. Basic block used in ResNet 18.

3.2. Training

We conducted experiments on our network, and used the pretrained model of ResNet18 on ImageNet for transfer learning. We froze the parameters of the feature extractor except for dual attention module after loading the pretrained model. The parameters of dual attention module and all fully connected layers are initialised randomly and continuously updated during the training process. All images are normalised before being inputted into the network, and are resized to 224×224 fitting the network. In addition, because the network is designed with two classification heads, multi-task loss is defined as follows:

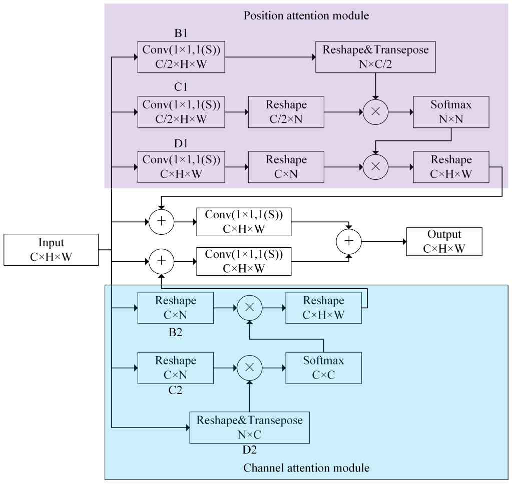


Figure 4. Architecture of dual attention.

$$L_{\text{shape}} = -\sum_{i=1}^{N} p_i \log(q_i) \tag{1}$$

$$L_{\text{color}} = -t_1 \log(s_1) - (1-t_1)\log(1-s_1) \tag{2}$$

$$L = L_{\text{shape}} + L_{\text{colour}} \tag{3}$$

The cross entropy loss of stool shape can be defined as Eq. (1)., where and are the ground truth and the predicted score for each class i in N , $N = 4$, it is the number of stool shape classes. In the binary classification for stool colour, where $N' = 2$, the binary cross entropy loss can be defined as Eq. (2), where it is meaning that there are two classes of stool colour: N'_1 and N'_2 . The t_1 and s_1 are the groundtruth and the predicted score for N'_1 , and $t_2 = 1 - t_1$ and $s_2 = 1 - s_1$ are the groundtruth and predicted score for N'_2 . The total loss L of our network is defined as Eq. (3), and it is equal to the sum between L_{shape} and L_{colour} . We trained our network for 30 epochs and used the stochastic gradient descent optimiser, the moment was set to 0.9, and the initial learning rate was set to 0.0001.

4. Experimental result and analysis

We evaluate our method on the dataset which is collected by volunteers and compare StoolNet performance with different networks. Then, we perform comprehensive studies to validate the effect of attention model used in our method.

4.1. Dataset description

Although previous studies for stool recognition have been proposed, there is still no available public stool

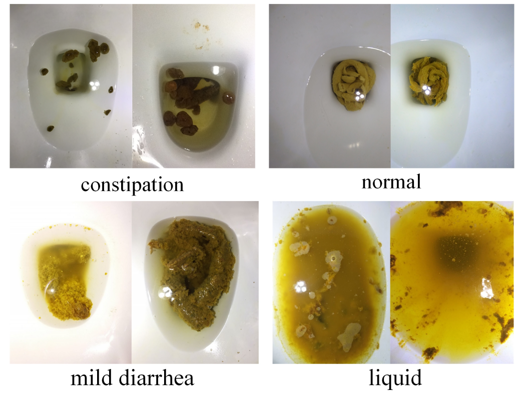


Figure 5. Examples for stool shape.

dataset, so we collected stool images by anonymous volunteers. After they used the toilet, we provided a piece of black cardboard (with a small hole) and placed the black cardboard about 1 metre above the toilet. The light on the individual's mobile phone was turned on and the light source was passed through the black cardboard. The small holes illuminate the stool area in the toilet, and then the phone camera is used to take pictures.

We invited two professional doctors to label the 1007 images collected based on seven categories of BSFS. Due to the small amount of data collected and the fact that the data do not follow a uniform distribution, according to the doctor's recommendations, we divided the data set into four categories: constipation (BSFS 1, 2), normal (BSFS 3, 4), mild diarrhoea (BSFS 5, 6), or liquid stools (BSFS 7), here we list BSFS 7 as a single category, as the category is completely watery in the real-life situation. In addition, doctors were invited to evaluate the colour of each stool image based on clinical practice experience. Representative images are shown in Fig. 5 and Fig. 6. Finally, the type distribution of the dataset we obtained is shown in Fig. 7, in which 76 images were abnormal in colour, and the remaining 931 images were normal.

4.2. Implementation details

All training process are completed in windows 10 using Pytorch framework with a single NVIDIA GeForce 1080 Ti GPU. In the experiments, we randomly selected training, validation, and test sets in the dataset at a ratio of 0.6, 0.2, and 0.2 for each class. There were 603, 202, and 202 images for the training, validation, and test sets respectively.

The collected images of each category are not uniformly distributed, so the training set and the validation set were enhanced. Considering classes of stool shape with a small number of images, only two classes used image augmentation: the constipation class is expanded to 10 times the original through horizontal and vertical flipping and random

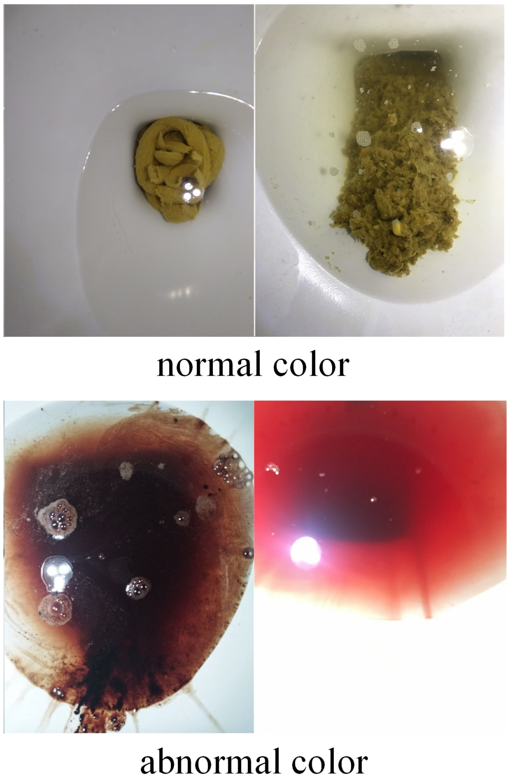


Figure 6. Examples for stool colour.

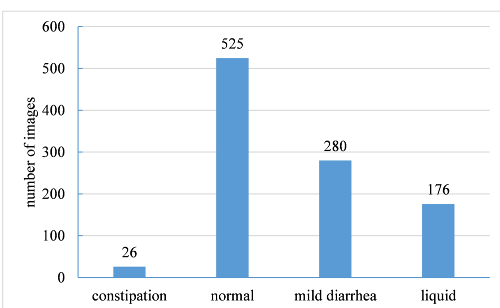


Figure 7. Stool image dataset.

rotation in the angle with range of 0 to 360; for the liquid class, this was expanded to 3 times the original through horizontal and vertical flips. The final training set contained 948 images, and the validation set contained 319 images.

4.3. Performance metrics

We used the metrics of accuracy and macro F1 score to assess the performance of StoolNet and other CNN methods. Where accuracy is defined as Eq. (4), it is the ratio of the number of correct recognitions to the number of images, and macro F1 is defined as Eqs. (4) to (8):

$$\text{accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$\text{Precision} = TP/(TP+FP) \tag{5}$$

$$\text{Recall} = TP/(TP+FN) \tag{6}$$

$$F1 = \frac{2^{*}\text{ Precision }^{*}\text{ Recall}}{\text{Precision } + \text{ Recall}} \tag{7}$$

$$\text{macroF } 1 = \frac{\sum_{i=1}^{N}(F1)^{i}}{N} \tag{8}$$

Where TP , True positive; TN, True negative; FP , False positive; FN , False negative. For the classification of stool shape, the macro F1 is equal to the average of F1 values of the four classes, $(F1)^{i}$ is the F1 value of the i-th classes. The reason for counting these data is to correctly evaluate our model. In terms of accuracy, even if some categories with a small number are completely misidentified, a good test result can still be obtained. However, this does not indicate that the model has better performance, so we counted macro F1 to avoid the above situation.

The dataset was randomly divided 5 times, and each divided dataset was trained 5 times in the networks. The average value of 25 test results (accuracy and macro F1) and 95% confidence interval (95% CI) are used as criteria for evaluating the performance of models. 95% CI is defined as Eqs. (9) to (11):

$$95\%CI = 1.95 * \frac{\sigma}{\sqrt{n}} \tag{9}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - u)}{n-1}} \tag{10}$$

$$u = \sum_{i=1}^{n} x_i/n \tag{11}$$

Where n is the number of tests, σ is standard deviation, u is mean value and x_i is i-th test result.

4.4. Main results

To evaluate our method on the stool image dataset collecting by volunteers, the training, validation and test set are randomly selected five times from the dataset and train all networks five times for each divided dataset. Finally, we calculated the average value of accuracy and macro F1 of our network in Tab. 1.

As a comparison and in order to avoid complex network reconstruction and training, we conducted experiments on different feature extractor and change it with the backbone of VGG19 [17], AlexNet [12], InceptionV3 [18], ResNet18,

	Shape		Colour	
Method	Accuracy ±95% CI	Macro F1 ±95% CI	Accuracy ±95% CI	Macro F1 ±95% CI
StoolNet	0.944±0.009	0.937±0.006	0.998±0.002	0.993±0.009

Table 1. Performance of the proposed model.

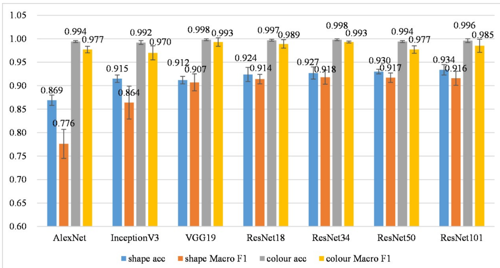


Figure 8. Performance comparison between different CNNs with freeze model. The freeze represents that froze the parameters of all convolutional layers after loading the pre-trained model.

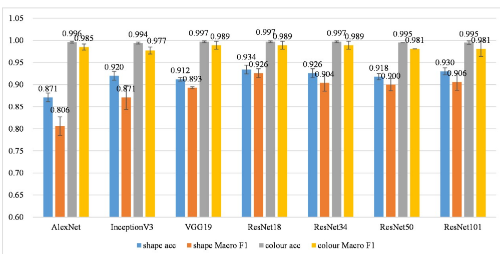


Figure 9. Performance comparison between different CNNs with update model. The update represents that the weight of the entire network is changed during the training process.

ResNet34, ResNet50 and ResNet101 [9]. Similarly, the transfer learning method is adopted and each feature extractor is connected to two classification heads which are the same with the proposed model. Furthermore, there were two main transfer learning methods we used: the first is same with the training process of the proposed model; the second, the parameters of all convolutional layers are initialised by the pre-trained model and the parameters of all fully connected layers are initialised randomly, then continuously updated the weight of the entire network during the training process. Stool images are resized into 299×299 for InceptionV3. For the remaining networks, the input images are resized to 224×224. Settings for training all networks are the same with the training process of our proposed model, as we described in section 3.2 and section 4.2.

As shown in Fig. 8 and Fig. 9, the results for freezing the convolution layer (which is called Freeze model) and updating all weight parameters (which is called update model) on the test set are nearly identical, especially for the classification of stool colour. The reason for the greater difference of the results on shape classification is because of the different network structures. ResNet18 with update mode and ResNet101 with freeze mode gave the highest accuracy of shape classification, reaching 0.934. However, for the macro F1 value of shape recognition is the best for ResNet18, reaching 0.926 (update mode). For the classification of stool colour VGG19 (freeze mode) and ResNet34 (update mode) gave the best result, however ResNet18 also gave a good result (get close to 100% and hard to improve performance further) and there are fewer parameters.

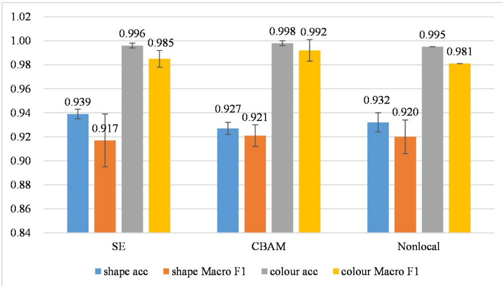
As a comparison, we chose to use the ResNet18 network as the baseline to modify the network structure and make an add-on study. We conduct experiments with sequeeze and excitation(SE) [10], convolutional block attention module (CBAM) [20] and nonlocal [19], and all of the three attention module are introduced into ResNet18 at the same place of dual attention module as we described in section 3.1. Then, the stool classification network was retrained. The parameter settings are the same as the former CNNs. The performance comparison between different attention blocks on the test set are counted in Fig. 10. Compared with the results counted in Table 1, our proposed model gave the best performance for the classification of stool shape and color.

We trained StoolNet and ResNet18 10 times, counted the results on the test set each time, and then defined the hypothesis H0 as there being no significant difference between StoolNet and ResNet18, while H1 shows that there is a significant difference between the two. The statistical significance level of was selected. The p-value is equal to 0.0001, and it is indicated that there is a significant difference between StoolNet and ResNet18.

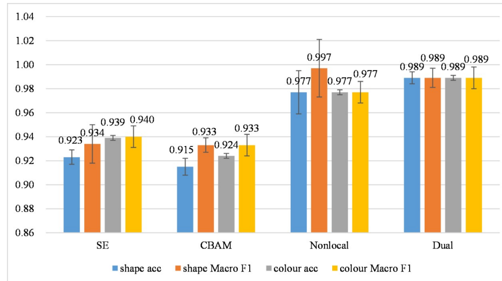
5. Conclusion

In this paper, we conducted the analysis of stool colour, combined with stool shape recognition. We have presented the SoolNet to perform multi-task classification of stool. It is based on ResNet18 making two classification head of stool colour and shape connected to the feature extractor in the network and add a dual attention block behind the last convolution layers of the network. Previous studies [8] and [14] used ResNet18 and InceptionV3 to classify the shape of stool into 3 categories. The test results show that our model reaches the current state-of-the-art performance.

We did not use a segmentation network to extract the faecal ROI in the image. Because, we believe that CNN has learned how to discard the background area in the image in the higher layer. If the segmentation network is used to extract the ROI area, then not only is the number of calculations unreasonably increased, the error segmentation in the early stage will also lead to the high error rate of the subsequent classification network. The improvement of our method benefits from data enhancement for only those few classes, instead of data enhancement for all classes, which



(a) freeze model.



(b) update model.

Figure 10. Performance comparison between different blocks introduced in ResNet18. All the blocks are introduced in StoolNet that is added behind the last convolution layers.

makes the model better for each category.

References

[1] Vijay Badrinarayanan, Alex Kendall, and Roberto Cipolla. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 39(12):2481–2495, 2017. 2

[2] MR Blake, JM Raker, and K Whelan. Validity and reliability of the bristol stool form scale in healthy adults and patients with diarrhoea-predominant irritable bowel syndrome. *Alimentary pharmacology & therapeutics*, 44(7):693–703, 2016. 1

[3] JW. Cha. Analysis of 2582 cases of routine stool examination results,. *J. Med*, 26(7):928–929, 2017. 1

[4] Chia-Fang Chung, Jonathan Cook, Elizabeth Bales, Jasmine Zia, and Sean A Munson. More than telemonitoring: health provider use and nonuse of life-log data in irritable bowel syndrome and weight management. *Journal of medical Internet research*, 17(8):e203, 2015. 2

[5] Carla E Flik, Yanda R van Rood, and Niek J de Wit. Systematic review: knowledge and educational needs of patients with irritable bowel syndrome. *European journal of gastroenterology & hepatology*, 27(4):367–371, 2015. 2

[6] Z. Lingli G. Jiangmei and Z. Yang. Analysis of results of routine fecal proexamination and 801 occult blood test in 1532 cases. *Lab. Med*, 12:98, 2009. 1

[7] Yan-Hong Gu, Koji Yokoyama, Koichi Mizuta, Takashi Tsuchioka, Toyoichiro Kudo, Hideyuki Sasaki, Masaki Nio, Julian Tang, Takayoshi Ohkubo, and Akira Matsui. Stool color card screening for early detection of biliary atresia and long-term native liver survival: a 19-year cohort study in japan. *The Journal of pediatrics*, 166(4):897–902, 2015. 1

[8] David Hachuel, Akshay Jha, Deborah Estrin, Alfonso Martinez, Kyle Staller, and Christopher Velez. Augmenting gastrointestinal health: A deep learning approach to human stool recognition and characterization in macroscopic images. *arXiv preprint arXiv:1903.10578*, 2019. 2, 6

[9] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 770–778, 2016. 3, 6

[10] Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7132–7141, 2018. 6

[11] Ravi Karkar, Jessica Schroeder, Daniel A Epstein, Laura R Pina, Jeffrey Scofield, James Fogarty, Julie A Kientz, Sean A Munson, Roger Vilardaga, and Jasmine Zia. Tummytrials: a feasibility study of using self-experimentation to detect individualized food triggers. In *Proceedings of the 2017 CHI conference on human factors in computing systems*, pages 6850–6863, 2017. 2

[12] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25:1097–1105, 2012. 5

[13] Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Arindra Adiyoso Setio, Francesco Ciompi, Mohsen Ghafoorian, Jeroen Awm Van Der Laak, Bram Van Ginneken, and Clara I Sánchez. A survey on deep learning in medical image analysis. *Medical image analysis*, 42:60–88, 2017. 2

[14] Seung-min Park, Daeyoun D Won, Brian J Lee, Diego Escobedo, Andre Esteva, Amin Aalipour, T Jessie Ge, Jung Ha Kim, Susie Suh, Elliot H Choi, et al. A mountable toilet system for personalized health monitoring via the analysis of excreta. *Nature biomedical engineering*, 4(6):624–635, 2020. 2, 6

[15] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. *International journal of computer vision*, 115(3):211–252, 2015. 2

[16] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014. 3

[17] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014. 5

[18] C Szegedy, V Vanhoucke, S Ioffe, J Shlens, and ZB Wojna. Rethinking the inception architecture for computer vision. In *2016 IEEE Conference on Computer Vision and Pattern Recognition*, volume 2016, pages 2818–2826. IEEE, 2016. 5

[19] Xiaolong Wang, Ross Girshick, Abhinav Gupta, and Kaiming He. Non-local neural networks. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7794–7803. IEEE, 2018. 6

[20] Sanghyun Woo, Jongchan Park, Joon-Young Lee, and In So Kweon. Cbam: Convolutional block attention module. In *Proceedings of the European conference on computer vision (ECCV)*, pages 3–19, 2018. 6

[21] Xu Zhang, Weiling Hu, Fei Chen, Jiquan Liu, Yuanhang Yang, Liangjing Wang, Huilong Duan, and Jianmin Si. Gastric precancerous diseases classification using cnn with a concise model. *PloS one*, 12(9):e0185508, 2017. 1