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Super resolution convolutional neural network based pre-processing for automatic polyp detection in colonoscopy images

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ABSTRACT

Colonoscopy is the most common methodology used to detect polyps on the colon surface. Increasing the image resolution has the potential to improve the automatic colonoscopy based diagnosis and polyp detection and localization. In this study, we proposed a pre-processing approach that uses convolutional neural network based super resolution method (SRCNN) to increase the resolution of the training colonoscopy images before the localization of polyps. We also investigated the use of CNN based models such as the Single Shot MultiBox Detector (SSD) and Faster Regional CNN (RCNN) for real-time polyp detection and localization. Our results showed that using SRCNN method before the training process provides better results in terms of accuracy in both models compared to the low-resolution cases. Furthermore, we reached an F2 score of 0.945 for the correct localization of colon polyps using Faster RCNN with ResNet-101 feature extractor.

1. Introduction

Colorectal cancer is among the top three leading causes of cancer-related deaths worldwide. Most colorectal cancers start with abnormal formations on the inner lining of the colon or rectum, which are called “polyps”. In order to detect and remove colon polyps before they turn into cancer colon polyps, several diagnostic approaches are preferred. Thus early diagnosis is essential for reducing the risk of mortality.

Colonoscopy is a well-known diagnostic procedure for detecting colon polyps. However, some of the polyps may be missed during the colonoscopy procedure. Moreover, physicians may need to interpret the images and videos to assess the patient’s health status after colonoscopy operation. This process may not detect the polyps or errors while diagnosing the malignant polyps. Thus, computer-aided detection of polyps is necessary during or after the colonoscopy procedure. Automatic detection of polyps may help the physicians reduce the examination time and cost, and improve the outcomes.

In recent years, a prominent progress has been achieved on object detection using convolutional neural networks (CNN), a popular

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deep learning (DL) approach. Modern object detectors based on CNN can be listed as faster region-based CNN (RCNN) [1], single shot MultiBox detector (SSD) [2], You-Only-Look-Once (YOLO) method [3], RefineDet [4], M2Det [5], Cascaded R-CNN with multiscale attention for traffic sign detection [6], watershed segmentation based detector for brain tumor detection [7], and variable precision rough set model (VPRSM) based algorithm for detection of outliers [8].

The region-based CNN approaches (RCNN); Fast RCNN and Faster RCNN have been shown to be feasible alternatives for object detection on colonoscopy image and video datasets. These methods adopt deep CNN architectures to automatically learn feature representations in detail. In the initial RCNN study [9], external region proposal methods were adopted, such as selective search and edge boxes, to train a CNN model. However, this method was slow in detecting the objects. Single stage CNN training by using region-of-interest (ROI) pooling technique was proposed in Fast RCNN to overcome the speed problem [10]. In Faster RCNN method, region proposal network (RPN) was used to improve detection performance in terms of accuracy and time. Moreover, Faster RCNN method was chosen for polyp detection using Inception ResNet feature extractor and data augmentation methods [10].

Deep learning is a proven technique to yield high classification accuracies on different medical images. Keras deep learning state-of-the-art image classifiers using CNN architecture were used for polyp prediction in endoscopy images [11, 12]. The findings show that pre-trained networks (such as VGG16, VGG19, ResNet, Inception-v3 and Xception) with Keras library were highly effective for classifying several types of polyps in wireless capsule endoscopy images [11]. Sornapudi et al. [12], used a modified region based CNN with pre-trained ResNet-50 and ResNet-101 feature extractor and fine tuning techniques to localize the colonic polyp images.

In medical field, super resolution (SR) has its own role. SR is the process of up-scaling and improving the details within an image, such as recovering a high-resolution image from a single low-resolution image. CNN based super resolution methods were used to improve the quality of medical images, and to learn a set of filters that allow mapping of low-resolution images to their high-resolution counterparts [13]. Pham et al. [14], has trained a CNN for MRI super resolution using visible light natural images. Chen et al. [15] proposed a three-dimensional (3D) multi-level Densely Connected Super-Resolution Networks (mDCSRN) with generative adversarial network (GAN) to obtain more accurate MRI super resolution images. Jurek et al. [16], performed a set of experiments and reported on the efficiency of CNN based image reconstruction for the improvement of diagnostic quality.

Applying different types of pre-processing approaches on the images has the potential to improve polyp detection performance. Deep learning based single image super resolution (SISR) method is one of the approaches used for this purpose. This method demonstrates that previous sparse-coding methods are effectively equivalent to applying deep CNN. However, the deep learning method is faster and is entirely end-to-end (no intermediary steps). Super Resolution Convolutional Neural Networks (SRCNN) is fully convolutional making them extremely fast. In addition, SRCNN possess a very simple CNN structure that provides noticeable performance improvement in terms of SISR results that are obtained using 2D natural images.

Here, we discuss the use of SRCNN model as the pre-processing method to improve the resolution of the colonoscopy images used in the training process for the first time in the literature as we know it. We investigated the effect of using SR approach on two popular object detection structures; SSD and Faster RCNN. We trained these networks with and without pre-processing, and compared their performances in terms of real-time polyp detection and localization accuracy. In Section 2, our proposed method and the image datasets are described in detail. The performances of deep learning based architectures for automatic polyp detection with two different resolution improvement approaches on two different test sets are presented in Section 3. Section 4 discusses the findings of

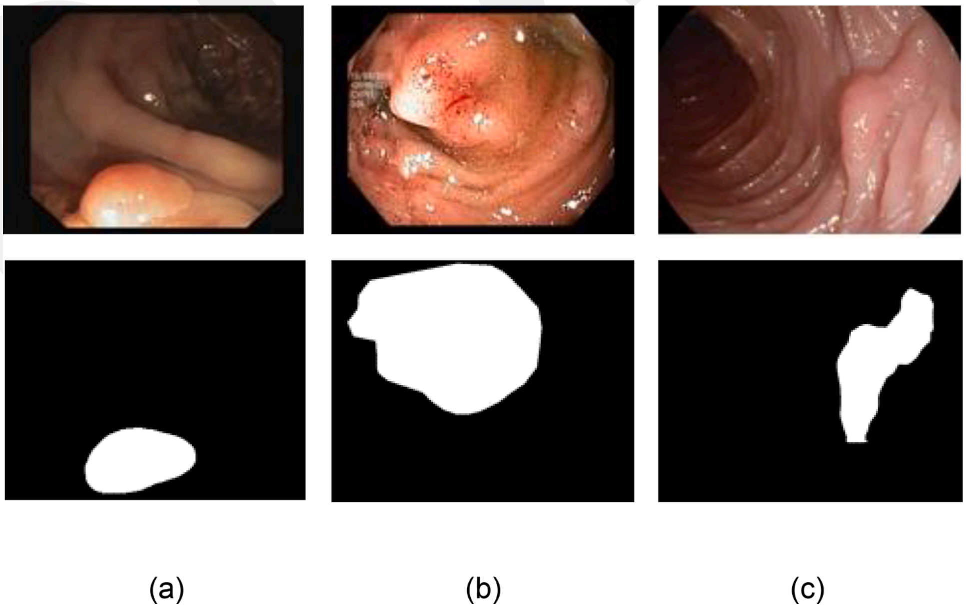

Fig. 1. Sample colonoscopy images and their ground truths covering the polyp from the CVC-Clinic (a), KVASIR (b) and ETIS-LARIB (c) databases, respectively.

this study and projected future work. The conclusion is provided in Section 5.

2. Materials and methods

2.1. Colonoscopy images

We used three different open-source databases; CVC-Clinic [17], KVASIR [18] and ETIS-LARIB [19] in this study. CVC-Clinic database was chosen as the training set, and KVASIR and ETIS-LARIB were selected as the test sets. CVC-Clinic database is consisted of 612 still images with a resolution of 388 × 284 pixels from 29 different sequences in standard definition (SD). KVASIR dataset is consisted of 1,000 different polyp images with a resolution of images between 720 × 576 and 1920 × 1072 pixels. ETIS-LARIB dataset contains 196 polyp images with a resolution of 1225 × 966 pixels which were extracted from 34 colonoscopy videos. Each image has its associated manually annotated ground truth image covering the polyp. Fig. 1 shows three sample images from CVC-Clinic, KVASIR and ETIS-LARIB databases with their corresponding ground truths, respectively.

2.2. Pre-processing

We used a CNN based single image super resolution SRCNN model [13]. The goal of this model is to learn a set of filters that allows to map low-resolution inputs to a higher resolution output. Therefore, we constructed two sets of image patches instead of actual full-resolution images. We started with a low-resolution patch that was used as the input to the network. A set of feature maps was then extracted by the first convolution layer of the SRCNN, followed by the nonlinear mapping of features to a high-resolution patch in the second layer. The last layer was used to reconstruct the final high-resolution image by using the predictions as shown in Fig. 2. We applied SRCNN model to the training set (CVC-Clinic database), and obtained new images with 446 × 413 pixel resolution. Thus, the resolution of our images was improved using this pre-processing method, and these high-resolution images served as the inputs for Faster RCNN and SSD networks. Detected polyp on colon surface was the output of these networks as presented in Fig. 3.

We also reported on the use of simple resizing of training images based on bilinear interpolation method. The input set was comprised of low-resolution images from the CVC-Clinic database and the output set included the images with improved resolution (the new images with a size of 446 × 413 pixels). This approach made it possible to compare the effects of employing SRCNN or simple resizing to increase the resolution of training images in the colon polyp localization problem.

2.3. Detection models

We proposed two different polyp detection architectures to determine the locations of the polyps automatically: SSD and Faster RCNN. These architectures are commonly used for object detection tasks because they have the capability to classify both an object inside the image and determine its specific location. Faster RCNN architecture is specifically notable for medical image analysis which eventually makes it preferable as a polyp localization approach. SSD is a popular algorithm, which was developed by Szegedy et al. [2]

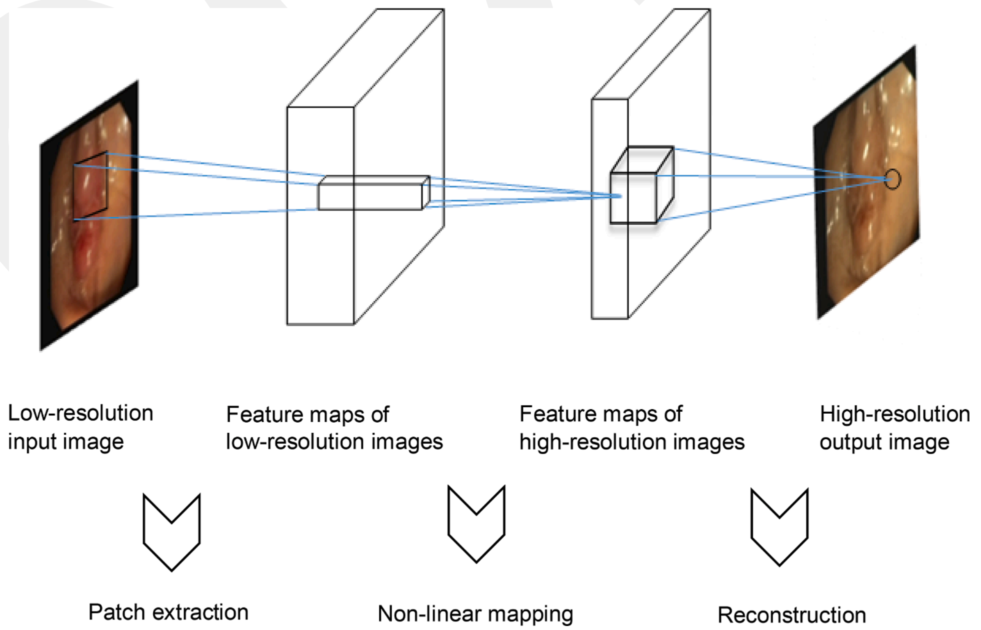

Fig. 2. Block diagram of the implemented pre-processing method [13].

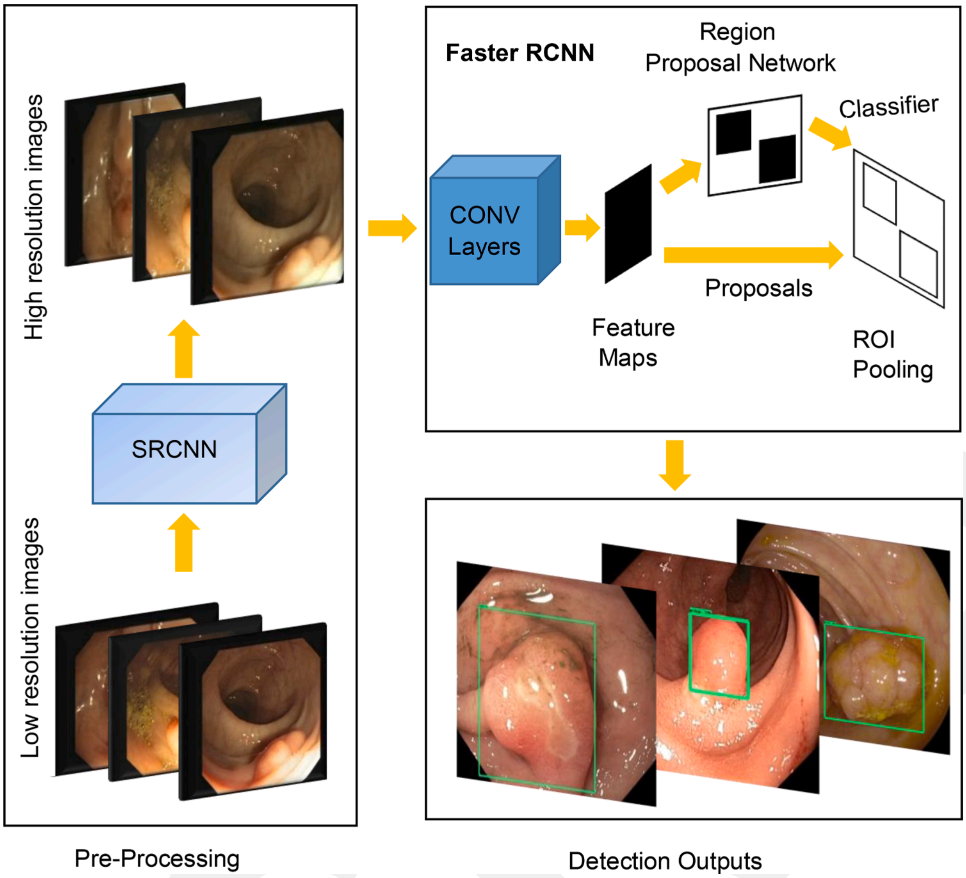

Fig. 3. Graphical representation of our CNN based super resolution model.

for object detection tasks in terms of performance and better precision on standard datasets such as PascalVOC and Microsoft Common Objects in Context (COCO) [2]. Faster RCNN has performed better in terms of accuracy compared to SSD approach in our case.

SSD architecture frequently uses the single feed-forward convolutional network. This network generates a fixed-size collection of bounding boxes and scores for the presence of object class instances in those boxes to precisely estimate classes and region box (anchor) offset without second step per proposal classification operation. Faster RCNN operates in two steps for detection process. First step is called as region proposal network (RPN) where features are extracted from images by using feature extractor such as VGG or ResNet. For class-agnostic box proposal generation, features at some selected intermediate level (conv5) are used. RPN ranks anchors and proposes the ones that are most likely containing objects. These box proposals are used to crop features from the same intermediate feature map (ROI pooling) in the second step. The features of box proposals are then subsequently fed to the rest of the feature extractor (fc6 followed by fc7) to predict a class by using multiway classification. It is preferred to order a set of options instead of choosing one and class-specific box refinement such as location and size for each proposal.

The diagrams for the detection methods are presented in Fig. 4. In the faster RCNN, the input image passes through the convolution layer and feature maps are extracted. Then, a sliding window is used in RPN for each location over the feature map. Anchor boxes (default bounding boxes) are used to generate region proposals for each location. The output of RPN is a set of rectangular object proposals that have a probability of containing the objects of interest. Bounding box labels that are assigned to the boxes and their probabilities (objectiveness score) for each label and box are obtained. After RPN, different size proposed regions are found. Thus, ROI pooling solves the problem by scaling down the feature maps into the same size.

Classifier layer determines the output of the system regardless of the presence of an object and the regression layer outputs for the box coordinates (box center coordinates, width and height). In this layer, regression is calculated while comparing the estimated bounding and the ground truth boxes.

We have also investigated these structures for two different feature extractors in terms of accuracy with and without pre-processing. We proposed the use of deep learning based image super resolution method as a pre-processing method. We used deep learning models with transfer learning scheme because of the limited number of images in our datasets. We performed SSD and Faster RCNN object detection models performed with Inception-v2 and ResNet-101 on Tensorflow platform to detect polyps in colonoscopy images.

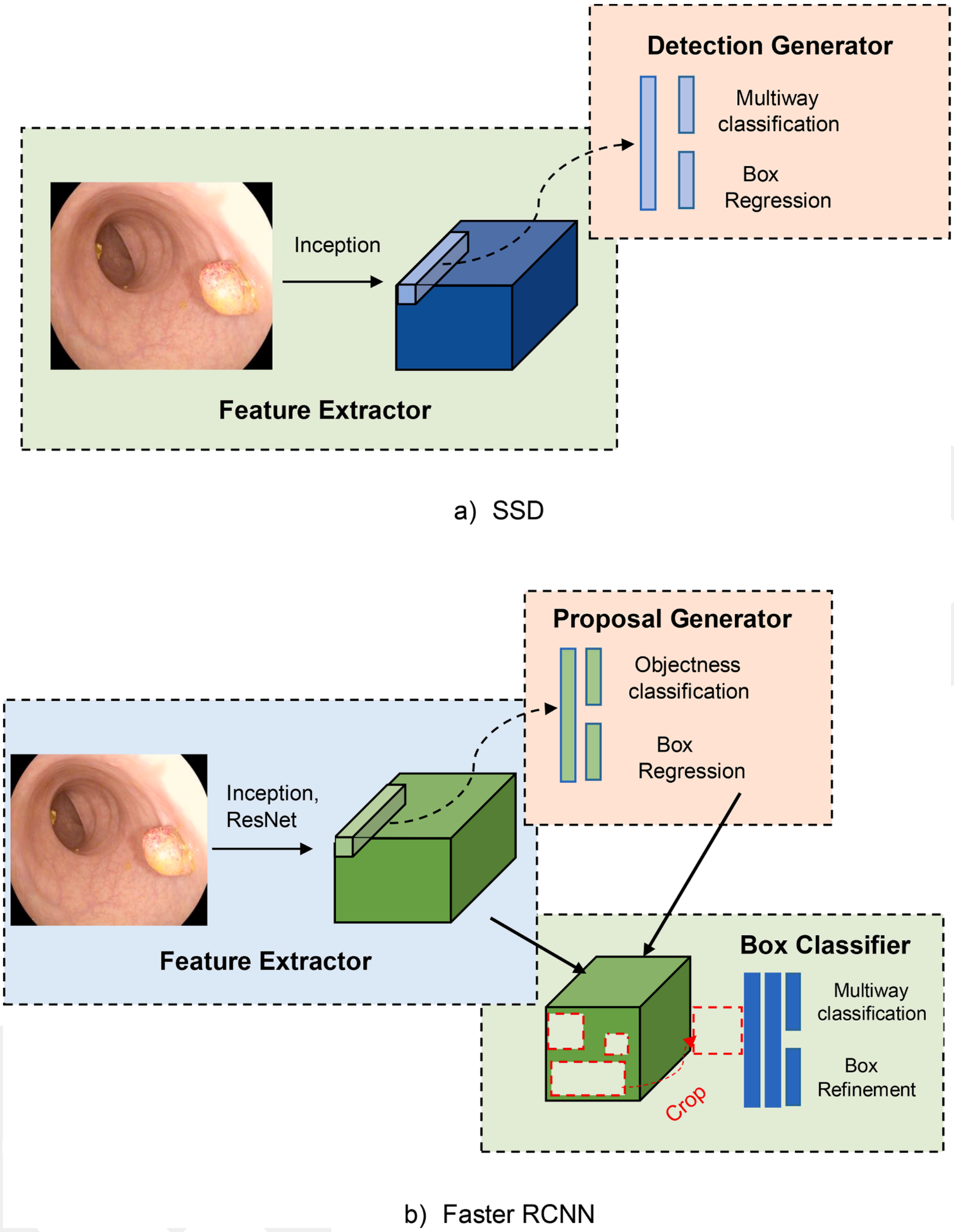

Fig. 4. Detection architecture diagrams [20].

2.4. Experimental stage for detection

Different deep learning frameworks namely DistBelief, Caffe and Torch are available. We preferred the Tensorflow platform, and used SSD and Faster RCNN with different feature extractors as training models for polyp detection. Tensorflow platform allowed us to easily alter different models and their parameters. Transfer learning, the method that we preferred does not require extremely large training dataset and computational power. COCO dataset that has been trained on 120,000 training and validation images belonging to 80 categories was preferred. The polyp detection system was trained with CVC-Clinic polyp database and initialized with pre-trained weights from COCO.

There are six commonly used models that have been trained on the ImageNet dataset as the feature extractors from open source Tensorflow implementations. We used ResNet-101 and Inception-v2 feature extractors for Faster RCNN, and also Inception-v2 feature extractor for SSD. In the Inception-v1 module, the main concept was that the network basically would get wider rather than deeper. Inception-v2 module was designed as an upgrade to v1 in order to increase the accuracy and reduce the computational complexity. ResNet-101 model has a deeper structure compared to other feature extractors. The primary advantage of a deeper structure is provide the extraction of more considerable information features over the image data. ResNet-101 suggests to skip the connection for moving input from the previous layer to the next layer without changing anything as the input.

CVC-Clinic and ETIS-LARIB datasets were performed for the training process and test, respectively. These dataset guidelines were compared to the methods that were presented in MICCAI 2015 [21]. CVC-Clinic dataset was used for the training process and the ETIS-LARIB dataset for the test. The same procedure was applied as the evaluation matrix. In the CNN based segmentation strategy that was adapted by CUMED [21], pixel-wise classification was achieved by ground truth polyp masks. AlexNet CNN model and the traditional sliding window approach for patch based classification were used by the OUS team [21]. A better recall has been observed in FCN-VGG due to the supply of more data by the use of CVC-Clinic and ASU-Mayo databases in the training process [22]. Mask RCNN with ResNet-101 was also employed for polyp detection and segmentation [23].

2.5. Performance metrics

Performance metrics proposed by the MICCAI 2015 sub-challenge [21] were used to evaluate the polyp detection results. These metrics are precision, recall, F1 and F2 score. When the polyp detection system correctly identified a polyp according to the ground truth, it was regarded as a true positive (TP). In the false positive (FP) case, the system detected the polyp that did not match the ground truth. When the system did not detect the polyp in the frame, it was regarded as a false negative (FN). There were no true negatives (TN), since there were no frames that did not include any polyps. The metrics were formulated as follows:

$$Precision\ (P) = \frac{TP}{TP + FP} \tag{1}$$

$$Recall\ (R) = \frac{TP}{TP + FN} \tag{2}$$

$$F1\ score = \frac{2 * P * R}{P + R} \tag{3}$$

$$F2\ score = \frac{5 * P * R}{4 * P + R} \tag{4}$$

We performed a statistical analysis to show whether that the differences in numerical results were statistically significant or not. For this purpose, we examined the KVASIR dataset which includes 1,000 images with polyps and randomly divided them into 10 equal-size subsets. We then computed F1 measures of each subset for each pre-processing approach. No processing, simple resizing, and SRCNN were computed for different models and feature extractors (SSD Inception-v2, Faster RCNN Inception-v2 and Faster RCNN ResNet-101). In the statistical comparison phase, we initially performed a normality test using Shapiro-Wilk and Kolmogorov-Smirnov tests on F1 values of subsets. Analysis of variance (ANOVA) test was subsequently implemented for three classes (based on pre-processing approach) to obtain statistical significance levels ($p<0.05$).

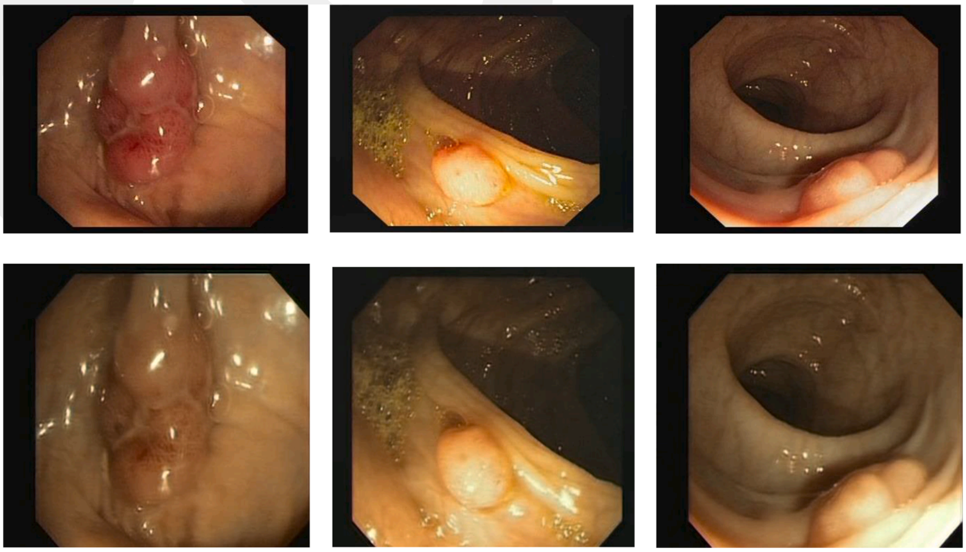

Fig. 5. First row demonstrates three low-resolution sample images in the CVC-Clinic database, and the second row indicates the high-resolution counterparts.

3. Results

We present our results based on the method we proposed. Fig. 5 shows the sample low-resolution sample images in the CVC-Clinic database and the output images of the SRCNN model with improved resolution. First row presents the original low-resolution images and the second row presents the high-resolution counterparts. In the training process, these images were used as the input for polyp detection system.

Our results regarding the use of Tensorflow object detection models for polyp detection were quite successful. Table 1 and 2 denote polyp detection performances obtained for different feature extraction structures with and without pre-processing while using ETIS-LARIB and KVASIR test sets, respectively. The polyp detection performances in terms of accuracy with pre-processing yielded better results regarding the F2 scores when compared to no pre-processing case for both test sets.

We also observed that SRCNN based pre-processing helped the localization performance better than simple image resizing did for Faster RCNN. In Table 2, Faster RCNN Inception-v2 and Faster RCNN ResNet-101 with simple image resizing method have high P value which is due to low TP and FP and high FN values. In the statistical comparison phase, the normality tests (Shapiro-Wilk and Kolmogorov-Smirnov) on F1 values of 10 subsets on KVASIR dataset indicated that the values were normally distributed. The ANOVA test for three classes (based on pre-processing approach) depicted that statistical significance levels were less than 0.05 ($p<0.05$) for all comparisons indicating that the differences in numerical results were indeed statistically significant.

As shown in Fig. 6, the green bounding boxes indicate successful polyp detection outcomes using SSD (first row) and Faster RCNN (second row) models. After applying image super resolution method as the pre-processing approach, the sample localization results on the test data are shown in Fig. 7.

The first three columns depict the polyp locations with green bounding boxes using Faster RCNN without pre-processing (first row) and with pre-processing (second row). The last column demonstrates an example using SSD in a similar format employed for Faster RCNN. No bounding boxes on the image indicates that localization was not possible on that image.

The results of our detection models based on SRCNN are summarized in Table 3. Performance metrics; Recall, F1 and F2 scores, yielded better results considering previous studies [21–23]. Our analysis clearly indicates that deep learning based pre-processing method in the training phase improves the accuracy of studied models.

The detectors we studied were reliable in localizing polyps; however, bubbles, reflection of light and colonoscopy instruments were detected as a polyp on certain frames as depicted in Fig. 8 (a), (b), (d), and (e). Another fault type we observed was that the system detected a part of intestine as a polyp, as depicted in Fig. 8 (c) and (f).

4. Discussion

In this study, we proposed an automatic polyp detection method using deep learning techniques to reduce the false prediction rates. We investigated the effect of improving the resolution of colonoscopy images in the training phase for polyp localization using the SRCNN approach with the goal that SRCNN is a feasible and successful way in polyp localization. We also compared SRCNN to an interpolation based image resizing method. The SSD and Faster RCNN were the polyp localization architectures with Inception-v2 and ResNet-101 feature extractors. We showed about two-fold increment in the resolution that can provide significant improvements in the polyp localization. Although several other networks can be used, we believe the methods that we used are sufficiently enough to support our hypothesis.

Recently, numerous studies have contributed to the automatic colon polyp detection tasks using deep CNN techniques. Researchers that used the open dataset of MICCAI 2015 challenge on polyp detection suggested a highly effective region based CNN model to determine the localization of polyps in colon intestine [10, 24]. According to the literature, the predictions of region based CNN model

Table 1
Polyp detection accuracies for different feature extractors and pre-processing schemes on ETIS-LARIB dataset.

Polyp Detection Models	P (%)	R (%)	F1	F2
SSD Inception-v2 no pre-processing	29.73	15.38	0.202	0.179
SSD Inception-v2 with simple image resizing	15.75	23.53	0.189	0.214
SSD Inception-v2 with SRCNN based pre-processing	54.32	27.67	0.366	0.307
Faster RCNN Inception-v2 no pre-processing	76.92	70.65	0.736	0.718
Faster RCNN Inception-v2 with simple image resizing	82.43	66.66	0.737	0.693
Faster RCNN Inception-v2 with SRCNN based pre-processing	66.83	76.96	0.72	0.747
Faster RCNN ResNet-101 no pre-processing	70.33	73.14	0.717	0.725
Faster RCNN ResNet-101 with simple image resizing	78.28	75.69	0.769	0.762
Faster RCNN ResNet-101 with SRCNN based pre-processing	**71.02**	**84.44**	**0.771**	**0.813**

Table 2
Polyp detection accuracies for different feature extractors and pre-processing schemes on KVASIR dataset.

Polyp Detection Models	P (%)	R (%)	F1	F2
SSD Inception-v2 no pre-processing	46.80	44.70	0.457	0.451
SSD Inception-v2 with simple image resizing	78.44	48.11	0.596	0.521
SSD Inception-v2 with SRCNN based pre-processing	91.56	54.16	0.68	0.589
Faster RCNN Inception-v2 no pre-processing	75.63	97.45	0.851	0.918
Faster RCNN Inception-v2 with simple image resizing	81.31	96.41	0.88	0.928
Faster RCNN Inception-v2 with SRCNN based pre-processing	79.44	97.85	0.877	0.935
Faster RCNN ResNet-101 no pre-processing	83.82	96.63	0.897	0.937
Faster RCNN ResNet-101 with simple image resizing	83.03	94.59	0.884	0.92
Faster RCNN ResNet-101 with SRCNN based pre-processing	**85.70**	**97.06**	**0.910**	**0.945**

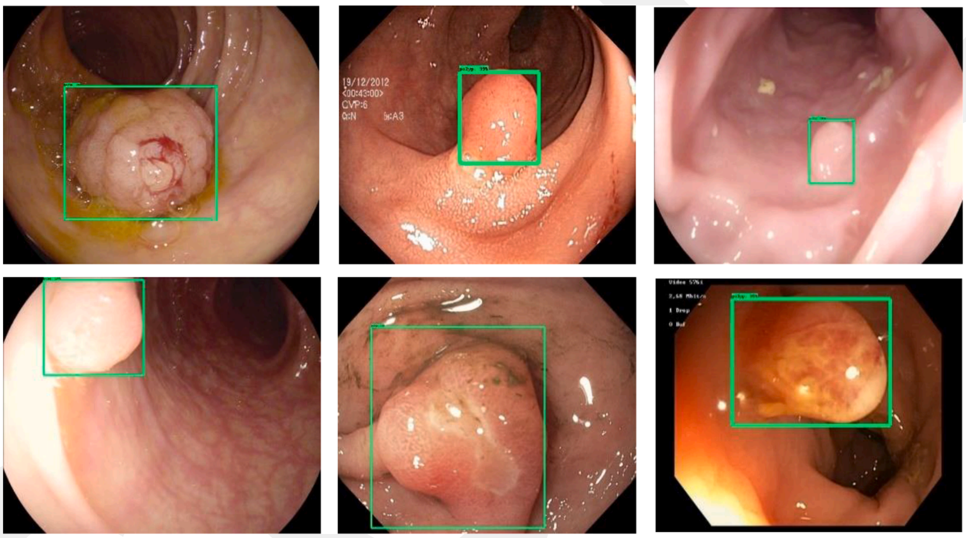

Fig. 6. Sample images for correct polyp localization using Faster RCNN and SSD.
First and second rows depict polyp detection results using SSD and Faster RCNN, respectively.

in general with transfer learning yielded highly impressive results in terms of F2 scores. The methods that we used for polyp detection provided similar results compared to the studies in terms of using transfer learning methods (ResNet-101, Inception-v2) on publicly available polyp datasets (CVC-Clinic, ETIS-LARIB and KVASIR). We obtained better F2 scores by using our pre-processing method compared to the previous works. In addition, we have compared two different polyp detection structures with different backbones. Our pre-processing method is simple and robust so it was easy to implement.

SRCNN has simple structured CNNs that can produce outstanding SISR results of 2D natural images. In recent years, more complex state-of-the-art super resolution methods applied on different medical images were also proposed other than SRCNN such as Super Resolution Generative Adversarial Network (SRGAN) [25], Enhanced Deep Super Resolution Network (EDSR) [26], Progressive Generative Adversarial Networks (P-GANs) [27], and Fast SRCNN [28]. We worked on a dataset with limited number of images that contain polyps. We are planning to expand our dataset with images that have no polyps, support various resolutions and improve the detection process by using above mentioned novel SR techniques for real-time applications.

In our research lab, we are targeting to gather clear/informative frames as a first identification step. We will then use these frames for localization and characterization of the polyp whether it is hyperplastic, adenomatous or serrated. The steps that we described above will be all in real-time. Our preliminary results are promising and show that our future work plan is feasible to implement.

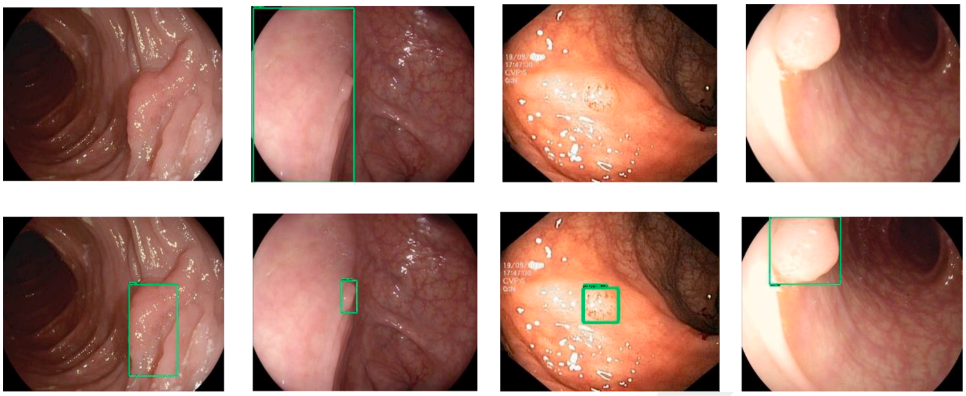

Fig. 7. Polyp localization results with and without pre-processing with SRCNN approach. The first three columns depict the polyp locations with green bounding boxes using Faster RCNN without pre-processing (first row), and with pre-processing (second row). The last column represents an example using SSD in a similar format employed for Faster RCNN.

Table 3
Polyp detection performance comparison to previous methods.

Detection Models	Precision (%)	Recall (%)	F1	F2
CUMED [21]	72.30	69.20	0.71	0.70
OUS [21]	69.70	63.00	0.66	0.64
FCN-VGG [22]	73.61	86.31	0.79	0.80
Mask RCNN w ResNet-101 [23]	80.00	72.59	0.76	0.74
Our Proposed Method	71.02	**84.44**	**0.77**	**0.81**

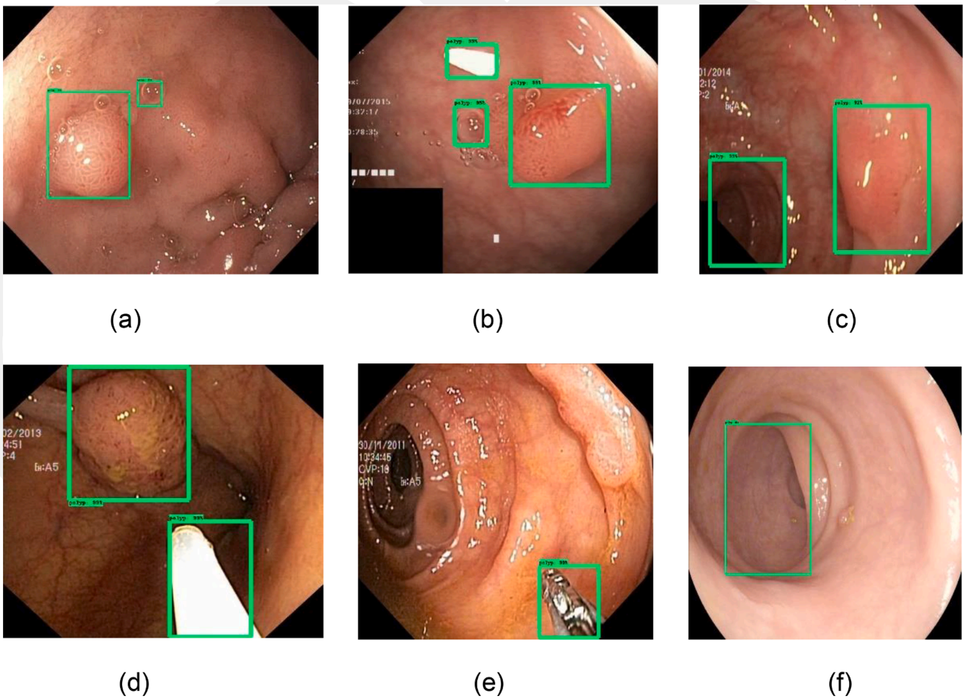

Fig. 8. Fault cases for the polyp localization system. Bubble, specular reflection, and colonoscopy instruments were detected as polyps in (a), (b), (d), (e). A part of the large intestine was detected as a polyp in (c) and (f).

5. Conclusion

The use of convolutional neural network based super resolution method (SRCNN) was presented as a pre-processing approach for deep learning based automatic polyp detection. We compared SRCNN and interpolation based image resizing approaches on the SSD and Faster RCNN models with Inception-v2 and ResNet-101 feature extractors for real-time polyp detection and localization using three publicly available image datasets. Our results showed that even a two-fold increment in resolution using SRCNN method before the training process provides better outcomes in terms of polyp localization accuracy in both models compared to the low-resolution counterparts. Furthermore, we reached an F2 score of 0.945 for the correct localization on Faster RCNN with ResNet-101 feature extractor when SRCNN is used. Our experimental results clearly indicate that the proposed method can achieve a high polyp detection performance on colonoscopy image datasets.

CRediT authorship contribution statement

Merve Taş: Conceptualization, Methodology, Software, Visualization, Data curation, Writing - original draft, Writing - review & editing. **Bülent Yılmaz:** Conceptualization, Investigation, Supervision, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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