Towards a comprehensive database to study the impact of image quality on abnormality detection and classification in Wireless Capsule Endoscopy

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Overview

Context

Example

In 2018, the Colorectal cancer (CRC) is the third (second respectively) leading cause of cancer death in the world (France, respectively).[1,2]

[1] Bray F, Ferlay J, Soerjomataram I, Siegel RL, Torre LA, Jemal A, "Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries", CA Cancer J Clin. 2018 Nov; 68(6):394-424.

[2] Faivre J, Dancourt V, et. al, Santé Publique France, "Cancer du colon rectum", https://www.santepubliquefrance.fr/maladies-et-traumatismes/cancers/cancer-du-colon-rectum

[3] McKESSON, "Colorectal Cancer & Laboratory Screening", 2018

Context

Example

In 2018, the Colorectal cancer (CRC) is the third (second respectively) leading cause of cancer death in the world (France, respectively).[1,2]

Solution

Studies have shown that early detection can result in up to a **92% survival rate for stage I of cancer.**[3]

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Wireless Capsule Endoscopy

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Wireless capsule endoscopy is a minimally **non-invasive** technology and effects better analysis of proximal and distal parts of the intestine compares to the classical endoscopy.

Objectives

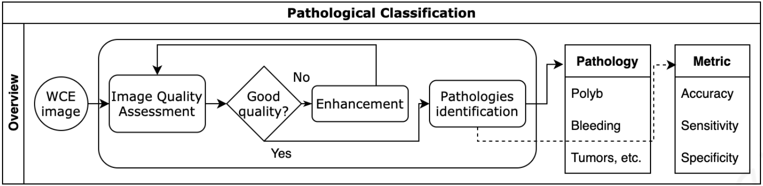

Figure 1: Model flowchart for overall algorithm to create a system to identify the name of pathologies

The main objective of the project is to develop a smart system for:

- Identify the pathologies on wireless capsule endoscopy (WCE) images
  - Including a pre-processing module that aims at improving the quality of the acquired images
  - Develop a set of image quality enhancement solutions based on various kinds of distortion

There are **many types of distortions** & in **different levels**

Challenges

- Some common acquisition distortions (**noise**, **blur**, **uneven illumination**, **specular reflection**) may affect the WCE based diagnosis. [4]

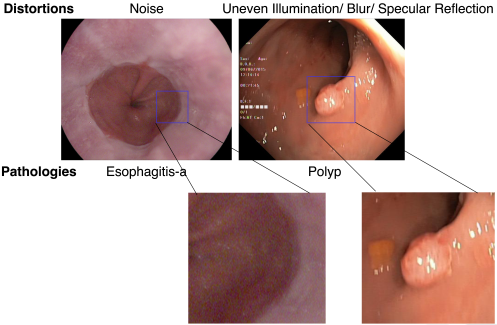

Figure 2: Illustration of some common WCE images distortions. Left column: *Esophagitis* image with Noise. Right column: *polyp* image with a combination of distortions including blur, uneven illmination and specular reflection.

[4] Borgli, H., Thambawita, V., Smedsrud, P.H. et al. *HyperKvasir*, a comprehensive multi-class image and video dataset for gastrointestinal endoscopy. Sci Data 7, 283 (2020). https://doi.org/10.1038/s41597-020-00622-y

How image **quality affects** the classification performance ?

Effect of distortion (Blur) on the object detection and counting [5]

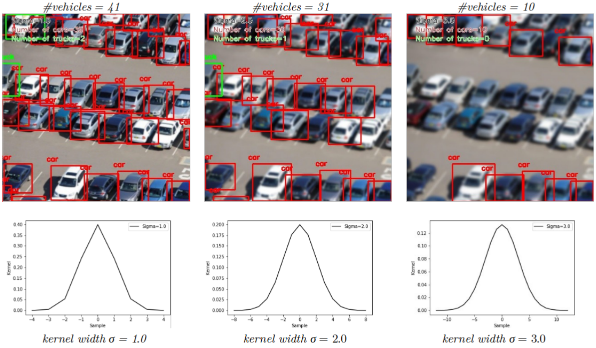

Figure 3: Degradation of the vehicle detection due to image blurring. Left column: Blurred image with kernel width $\sigma = 1.0$ detects 41 vehicles. Middle column: Blurred image with kernel width $\sigma = 2.0$ detects 31 vehicles. Right column: Blurred image with kernel width $\sigma = 3.0$ detects 10 vehicles.

[5] Borel-Donohue, Christoph and S. Young. "Image quality and super resolution effects on object recognition using deep neural networks." Defense + Commercial Sensing (2019).

Effect of distortion (Noise) on the object detection and counting [6]

Figure 4: Vehicle detections for additive noise with $SNR = 1.81, 4.39, 10.24$.

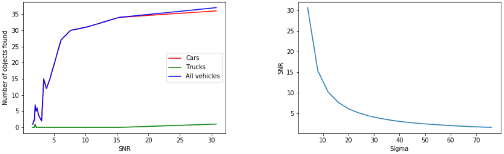

Figure 5: Number of cars detected as a function of the Gaussian noise added with a signal to noise $SNR = 1.62, ..., 30.76$. Right: SNR as a function of $\sigma = 4, 8, ..., 80$.

[6] Borel-Donohue, Christoph and S. Young. "Image quality and super resolution effects on object recognition using deep neural networks." Defense + Commercial Sensing (2019).

Effect of distortion (Noise, Blur) on the classification performace [7]

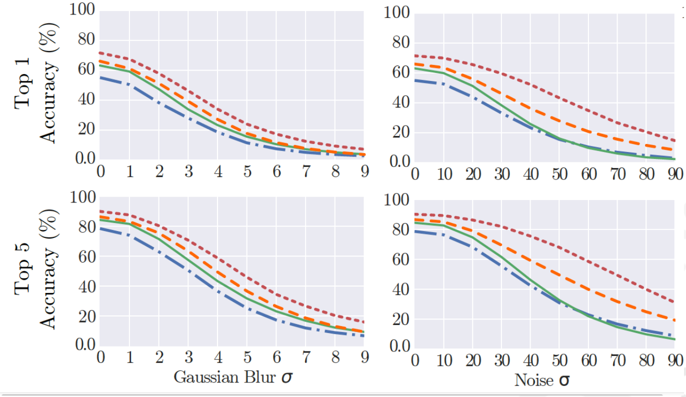

Figure 6: Top-1 and Top-5 Accuracy rates under different quality distortions. The networks are very sensitive to changes in blur and noise

[7] Dodge, Samuel F. and Lina Karam. "Understanding how image quality affects deep neural networks." 2016 Eighth International Conference on Quality of Multimedia Experience (QoMEX) (2016): 1-6.

How can we handle the distortions to enhance the image quality, hence improving the classification performace?

Method

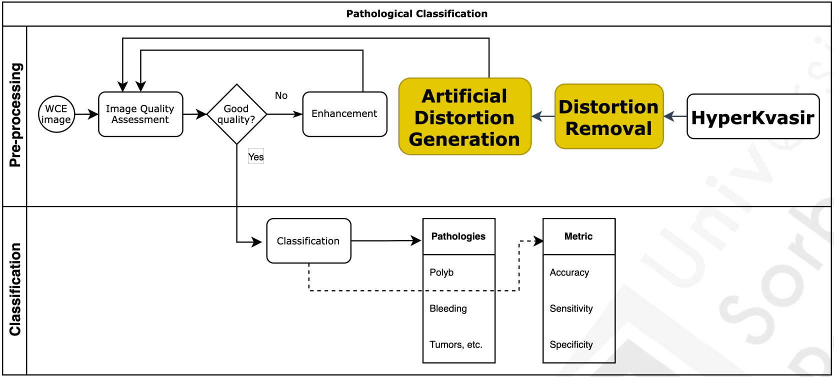

Figure 7: Flow chart of the pathological classification process

Existing datasets

Table 1: An overview of existing GI datasets.

Dataset	Findings	Size
CVC-356 [1]	Polyps	356 images
CVC-ClinicDB (also named CVC-612) [2]	Polyps	612 images
CVC-VideoClinicDB (also named CVC-12k) [1]	Polyps	11954 images
CVC-ColonDB [1]	Polyps	380 images
Endoscopy Artifact detection 2019 [3]	Endoscopic Artifacts	5,138 images
ASU-Mayo polyp database [4]	Polyps	18,781 images
ETIS-Larib Polyp DB [5]	Polyps	196 images
KID [6]	Angiectasia, bleeding, inflammations, polyps	2371 images and 47 videos
GIANA 2017 [7]	Polyps & Angiodysplasia	3462 images and 38 videos
GIANA 2018 [8]	Polyps & Small bowel lesions	8262 images and 38 videos
GASTROLAB [9]	GI lesions	Some 100s of images andfew videos
WEO Clinical Endoscopy Atlas [10]	GI lesions	152 images
GI Lesions in Regular Colonoscopy Data Set [11]	GI lesions	76 images
Atlas of Gastrointestinal Endoscope [12]	GI lesions	1295 images
El salvador atlas of gastrointestinal video endoscopy [13]	GI lesions	5071 video clips
Kvasir [14]	Polyps, esophagitis, ulcerative colitis, Z-line,pylorus cecum, dyed polyp, dyed resection margins, stool	8000 images
Kvasir-SEG [15]	Polyps	1000 images
Nerthus [16]	Stool - categorization of bowel cleanliness	21 videos

[8] Borgli, Hanna et al. "HyperKvasir, a comprehensive multi-class image and video dataset for gastrointestinal endoscopy". Scientific Data 7 (2020)

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They are rather small, and often limited to polyps. Several of these have also lately become unavailable.

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Using **HyperKvasir**[8] [17] dataset

[8] Borgli, Hanna et al. "HyperKvasir, a comprehensive multi-class image and video dataset for gastrointestinal endoscopy". Scientific Data 7 (2020)

HyperKvasir dataset

Table 2: Overview of the data records in the HyperKvasir dataset.

Data Record	# Files	Description
Labeled images	10,662 images	8 pathologies
Segmented Images	1,000 images	Segmentation masks for polyp findings
Unlabeled Images	99,417 images	Unlabeled
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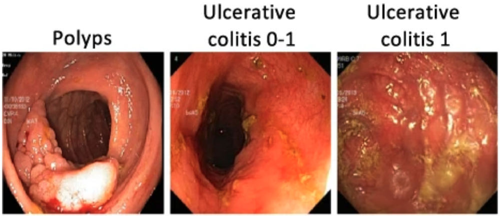


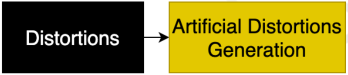
Figure 8: Image examples of the various labeled classes for images and/or videos.

Ongoing work

Our work has three stages including:

1. Remove the existing distortion in HyperKvasir dataset
2. Create the model to generate the new artificial distortions
3. Add the new artificial distortions to the distortions-free images.

1 Remove the existing distortions



2 Create the artificial distortions model

3 Add the artificial distortions to the distortions-free image

1. Remove the existing distortion in HyperKvasir dataset

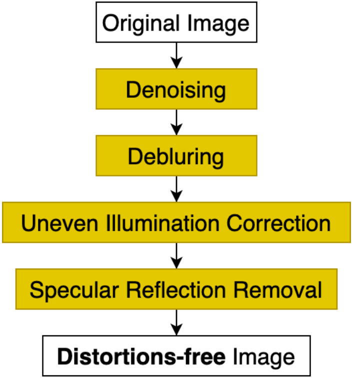
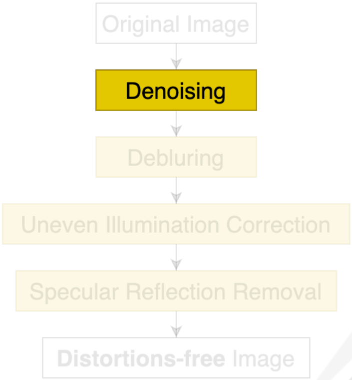


Figure 9: Process to remove the existing distortion in HyperKvasir dataset. The original image will go through four enhancement blocks corresponding to four common distortions: Noise, Blur, Uneven Illumination and Specular Reflection.

1.1 Denoising



Noise standard deviation estimation

For an image I with width W and height H, the estimated standard deviation σ_n of noise is estimated as[9]:

$$\sigma_n = \sqrt{\frac{\pi}{2}} \frac{1}{6(W-2)(H-2)} \sum_{x,y} |I(x,y) * M_N| \tag{1}$$

where $M_N = 2(L_2 - L_1)$ with the given L_1, L_2:

$$L_1 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{2}$$

$$L_2 = \begin{bmatrix} 1 & 0 & 1 \\ 0 & -4 & 0 \\ 1 & 0 & 1 \end{bmatrix} \tag{3}$$

[9] Immerkær, John. "Fast Noise Variance Estimation." Comput. Vis. Image Underst. 64 (1996): 300-302.

Autoencoder used for denoising

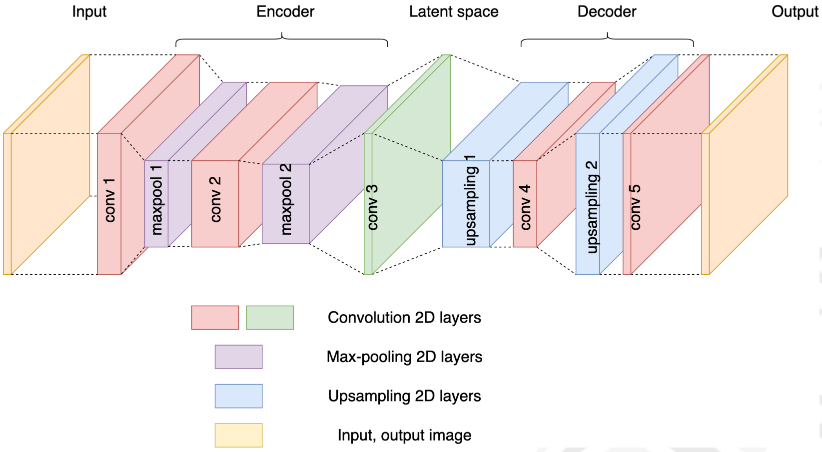


Figure 10: The Autoencoder model used for denoising

Results on Image denoising

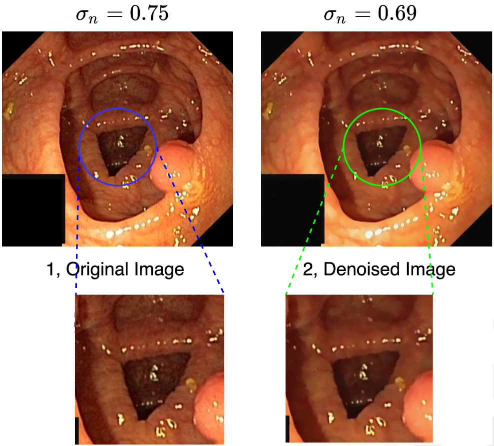
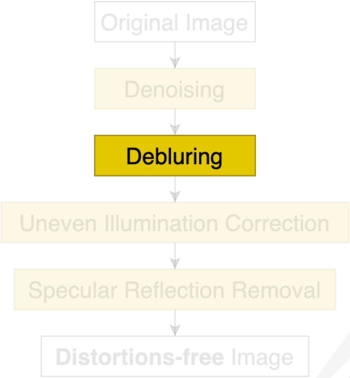


Figure 11: The results of the denoising experiment. The estimated noise standard deviation after denoising has been decreased showing the effectiveness of denoising method.

1.2 Debluring



Blurring index to estimate the level of blur

Apply the **variance of the Laplacian**[10][18] method to your own images to detect the amount of blurring.

$$index_b = var(\mathcal{L}(f(x,y))), \qquad (4)$$

where $f(x,y)$ is the input image

[10] Pertuz, Said et al. "Analysis of focus measure operators for shape-from-focus." Pattern Recognit. 46 (2013): 1415-1432.

DeblurGAN-v2[11] model for deblurring

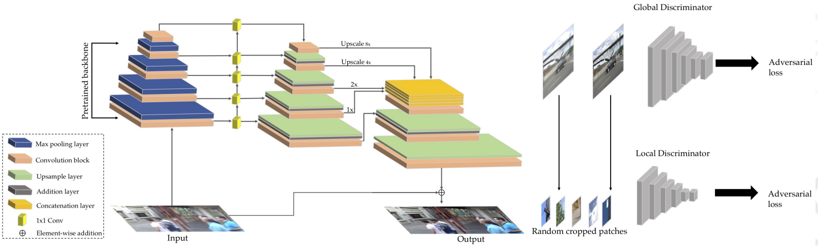


Figure 12: The DeblurGAN v2 model used for deblurring [19]

[11] Kupyn, Orest et al. "DeblurGAN-v2: Deblurring (Orders-of-Magnitude) Faster and Better." 2019 IEEE/CVF International Conference on Computer Vision (ICCV) (2019): 8877-8886.

Results on image deblurring

$index_b = 321$ $\quad$ $index_b = 416$

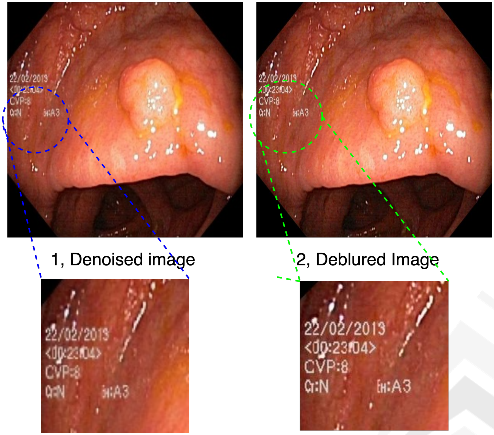
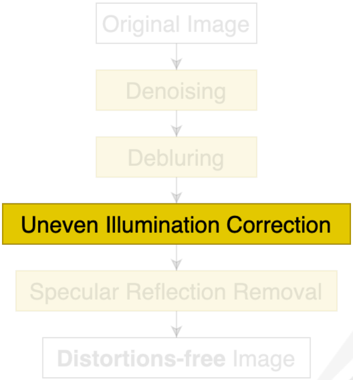
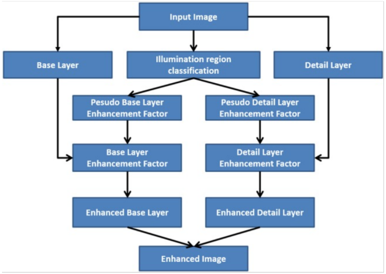


Figure 13: The deblured result. The Laplacian index after deblurring has been increased. The region of number shows clearly effectiveness of deblurring method.

1.3 Uneven Illumination Correction



Uneven Illumination correction[12] process



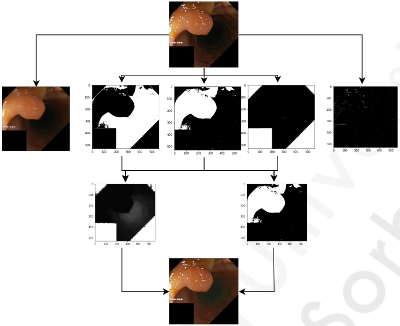


Figure 14: Uneven Illumination Correction process using [20]

[12] Xia, Wenyao et al. "Endoscopic image enhancement with noise suppression." Healthcare Technology Letters 5 (2018): 154 - 157.

Results on Uneven Illumination Correction

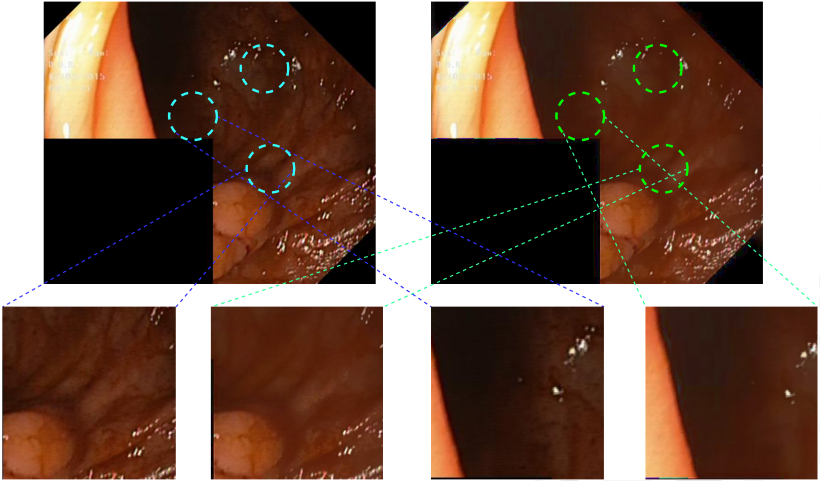
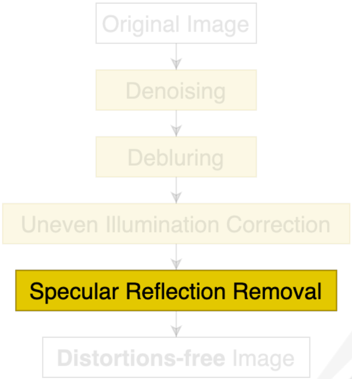


Figure 15: Uneven Illumination Correction result. The first row is the original image with the some uneven illmination region (cyan circle). In the second column, these regions have been corrected (green circle)

1.3 Specular Reflection Removal



Specular Reflection removal[13]

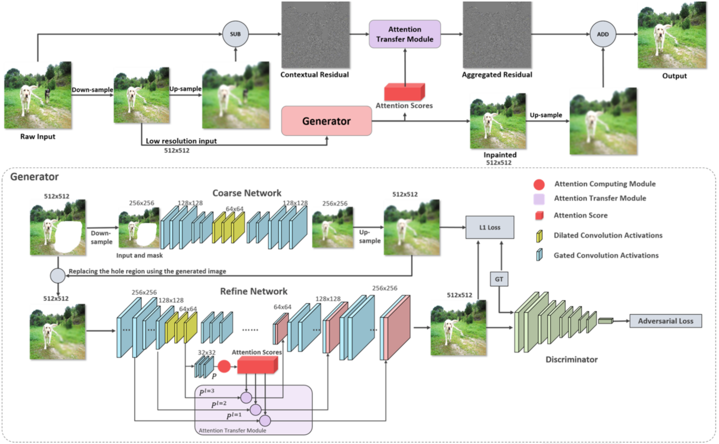


Figure 16: The overall pipeline of the method: (top) Contextual Residual Aggregation (CRA) mechanism, (bottom) the architecture of the generator [21]

[13] Yi, Zili et al. "Contextual Residual Aggregation for Ultra High-Resolution Image Inpainting." 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2020): 7505-7514.

Results on Specular Reflection Removal

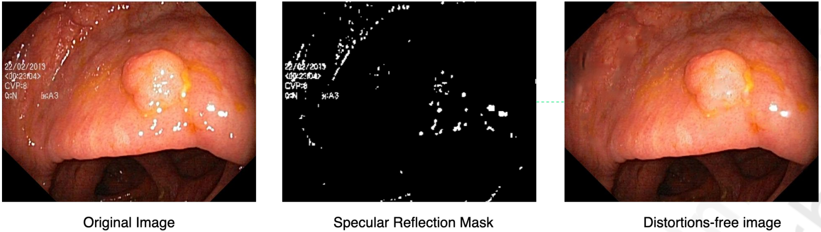
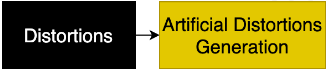


Figure 17: Specular Reflection Removal result. First columns: the input image with specular references. The third column is the result of the Specular Reflection inpainted image using the SR mask (second column) inspried from [22].

2. Generating artificial distortions and creating distorted image with controlled levels of distortions

- Create a model to generate the artificial distortions
- Add the artificial distortions to the distortions-free images

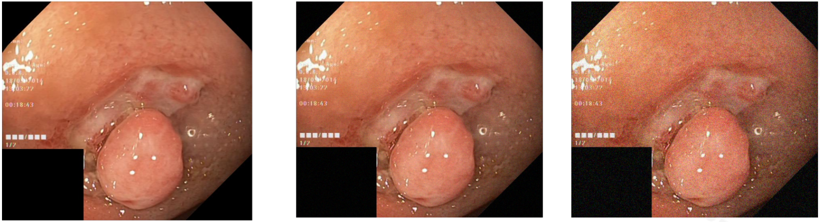
1 Remove the existing distortions



2 Create the artificial distortions model

3 Add the artificial distortions to the distortions-free image

2.1 Result images after adding Noise



Original Image

AWGN kernel width $\sigma_n = 0.01$

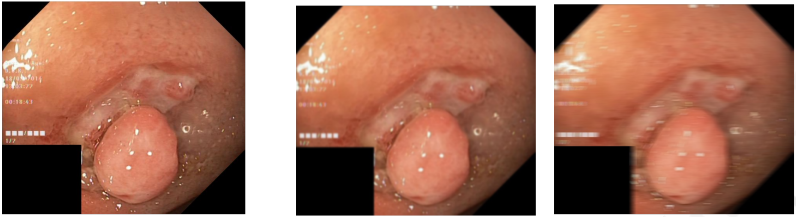
AWGN kernel width $\sigma_n = 0.1$

Figure 18: Creation of noisy image with controlled Gaussian Noise $n \sim N(0, \sigma_n^2)$

$$\hat{I} = I + n, \tag{5}$$

where n is the Gaussian noise which distributed according to the Gaussian distribution $N(0, \sigma_n^2)$.

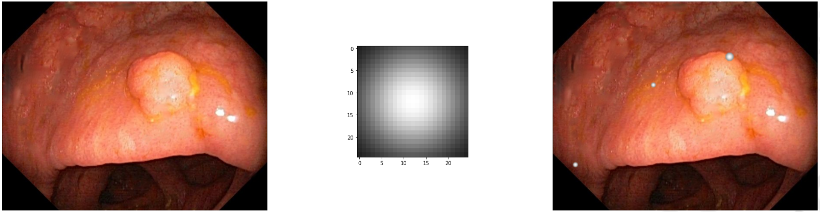
2.2 Result images after adding Blur



Original Image | Defocus blur kernel width $\sigma_{db} = 2$ | Motion blur kernel width of PSF $d_{mb} = 20$

Figure 19: Bluring image with Defocus Blur $b \sim N(0, \sigma^2_{db})$ and motion blur PSF kernel width d_{mb}

2.3 Result images after adding Specular Reflection



Input image | Artificial SR mask | Output Image

Figure 20: Artificial Specular Reflection by using the artificial SR mask with the random position

References

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[4] Nima Tajbakhsh, S. Gurudu, and Jianming Liang. "Automated Polyp Detection in Colonoscopy Videos Using Shape and Context Information". In: **IEEE Transactions on Medical Imaging** 35 (2016), pp. 630–644.

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[19] Orest Kupyn et al. "DeblurGAN-v2: Deblurring (Orders-of-Magnitude) Faster and Better". In: **2019 IEEE/CVF International Conference on Computer Vision (ICCV)** (2019), pp. 8877–8886.

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Thank you for watching!

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