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

1 Motivation & Context
- Context
- Wireless Capsule Endoscopy
  - Challenges
  - Solutions

2 Existing datasets
- Existing GI datasets
- HyperKvasir dataset

3 Our work
- Method
- Results

Context

Alert

Colorectal cancer is a major health problem.

[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

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Colorectal cancer is a major health problem.

Example

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

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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

Traditional endoscopy is often unpleasant and uncomfortable for the patient, can be painful, often requires moderate or deep sedation

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Wireless capsule endoscopy include its **non-invasive** character and its ability to visualize proximal and distal parts of the intestine

Objectives

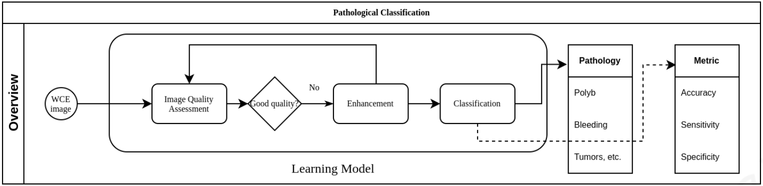

Figure 1: Model flowchart for overall algorithm to create a system to identify the name of pathologies

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 kinds of distortion

There are **many kinds of distortion** & in **different levels**

Challenges

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

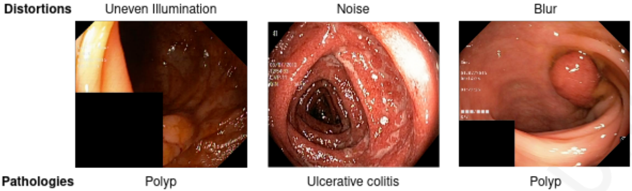

Figure 2: Illustration of some common WCE images distortions. Left column: *polyp* image with uneven illumination. Middle column: *ulcerative colitis* image with noise. Right column: *polyp* image with blur.

[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 classification performace [5]

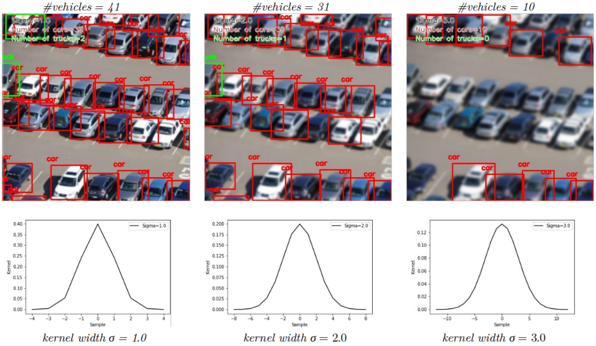

Figure 3: Degradation of the vehicle detection due to image blurring. Left column: Blurred image with kernel width $\sigma = 1.0$ detects 41 vehicles. Middle column: Blurred image with kernel width $\sigma = 2.0$ detects 31 vehicles. Right column: Blurred image with kernel width $\sigma = 3.0$ detects 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 classification performace [6]

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

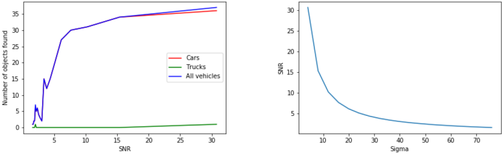

Figure 5: Number of cars detected as a function of the Gaussian noise added with a signal to noise $SNR = 1.62, ..., 30.76$. Right: SNR as a function of $\sigma = 4, 8, ..., 80$.

[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]

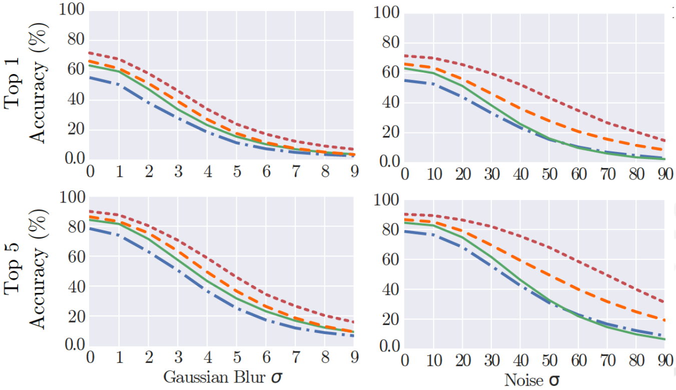

Figure 6: Top-1 and Top-5 Accuracy rates under different quality distortions. The networks are very sensitive to changes in blur and noise

[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.

Method

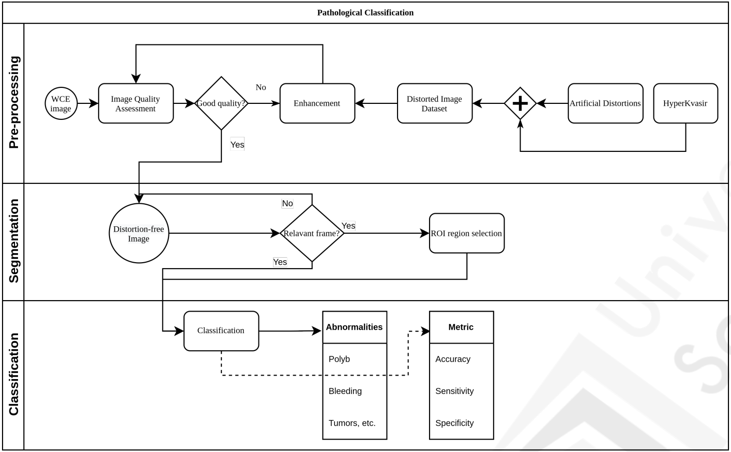

Figure 7: Flow chart of the pathological classification process

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

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Using **HyperKvasir** [17] dataset

HyperKvasir dataset

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

Data Record	# Files	Description
Labeled images	10,662 images	23 classes of findings
Segmented Images	1,000 images	Segmentation masks for polyp findings
Unlabeled Images	99,417 images	Unlabeled
Videos	374 videos	30 different classes

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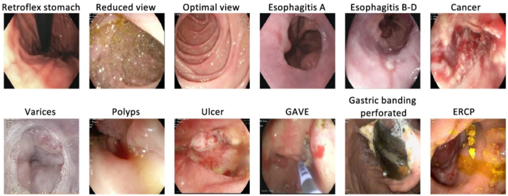
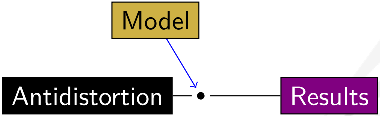


Figure 8: Image examples of the various labeled classes for images and/or videos.

Ourwork

Our work has three stages including cleaning the existing distortion in HyperKvasir dataset, then we create the model to generate the new artificial distortions. Finally, we add the new artificial distortions to the antidistorted images.

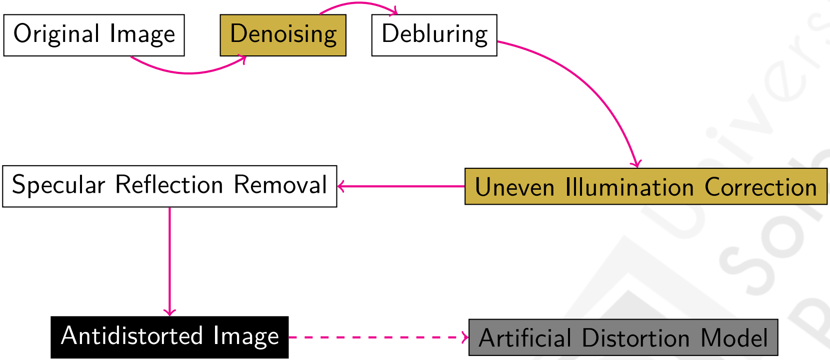
a) Clean the image *b) Create model*



c) Add artificial distortion

Results

Stage 1: we have to clean the existing distortion in the HyperKvasir dataset.



Results on Image denoising

For an image I with width W and height H, the estimated standard deviation σ_n of noise is estimated as[8]:

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

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

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

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

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

Results on Image denoising

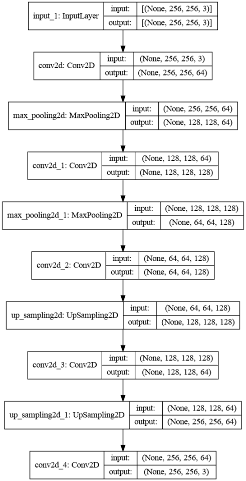
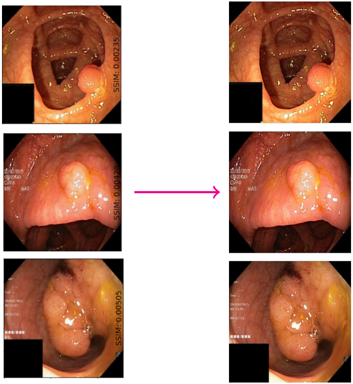


Figure 9: The Autoencoder model used for denoising

Results on Image denoising

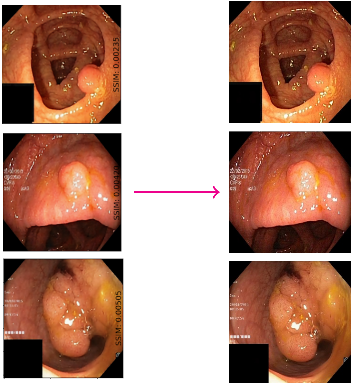
a) Original image

Results on Image denoising



a) Original image *b) Denoised image*

Results on Image denoising



a) Original image *b) Denoised image*

	Original image	Deblured- mage
First exp	0.75	0.7
Second exp	1.45	0.96
Third exp	1.1	0.90

Table 5: The estimated noise standard deviation before and after denoising.

Results on Image deblurring

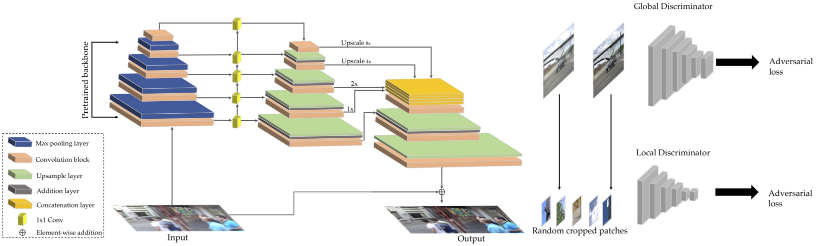


Figure 10: The DeblurGAN v2 model used for deblurring [18]

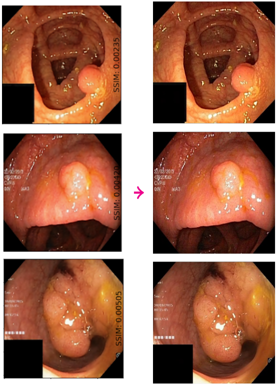
Results on Image deblurring

- Blur

a) Denoised

Results on Image deblurring

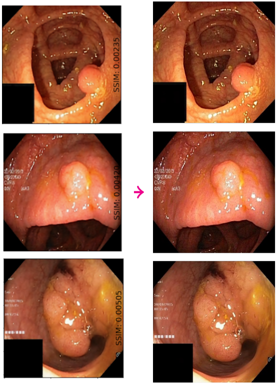
- Blur



a) Denoised *b) Deblurred*

Results on Image deblurring

- Blur



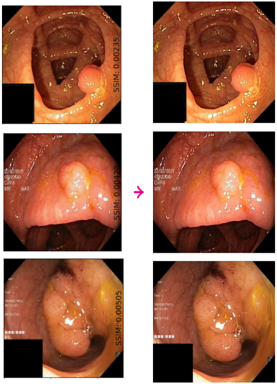
a) Denoised *b) Deblurred*

$$index = var(\mathcal{L}(f(x, y)))$$

*Apply the **variance of the Laplacian**[19] method to your own photos to detect the amount of blurring.*

Results on Image deblurring

- Blur



a) Denoised *b) Deblurred*

	Denoised-image	Deblured- mage
First exp	378	501
Second exp	321	428
Third exp	224	367

Table 5: The variance Laplacian Index before and after deblurring.

Results on Uneven Illumination Correction

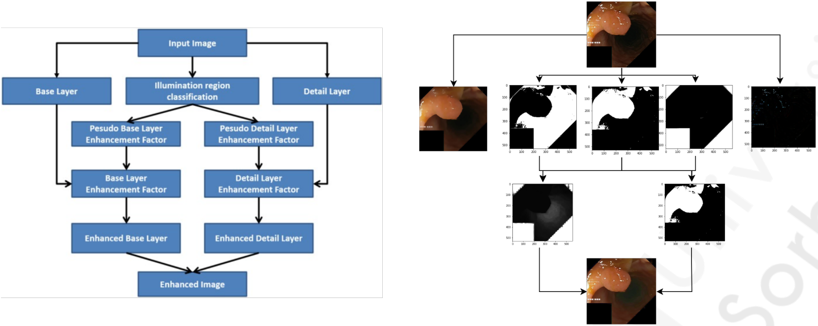


Figure 11: Uneven Illumination Correction process using [20]

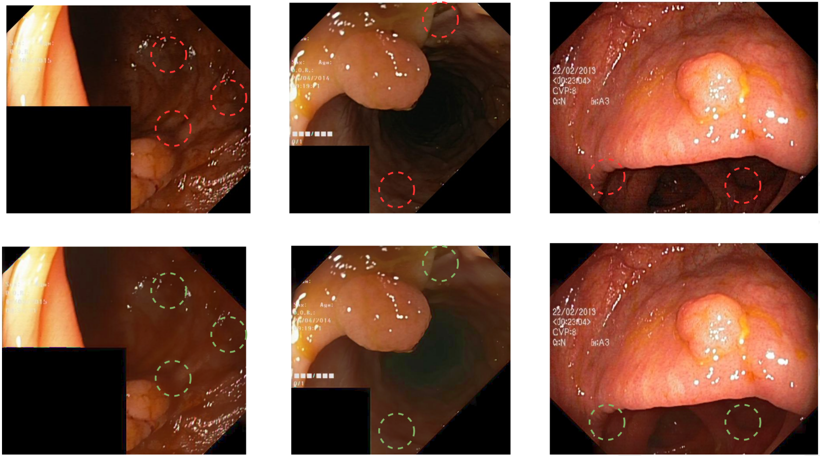


Figure 12: Uneven Illumination Correction result. The first row is the original image with the some uneven illmination region (red circle). In the second column, these regions have been corrected (green circle)

Results on Specular Reflection Removal

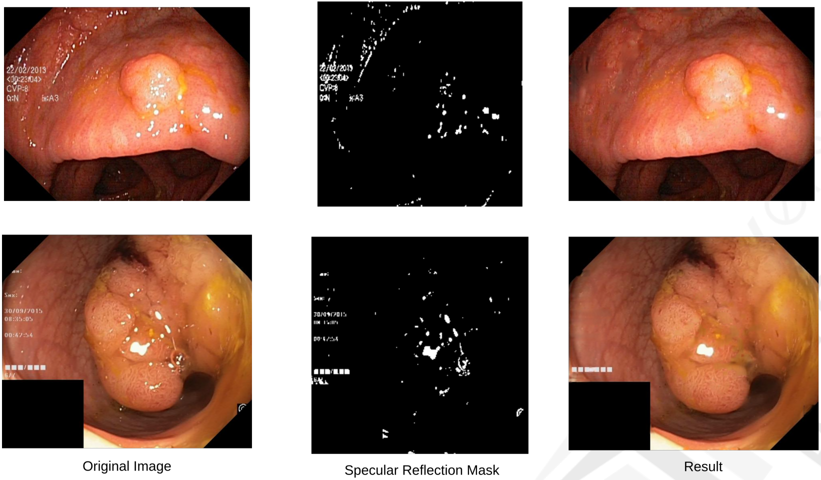


Figure 13: Specular Reflection Removal result. First columns: the input image with specular references. The third column is the result of the Specular Reflection inpainted image using the SR mask (second column) inspried from [21].

Results

In this work, we create a model to add the artificial distortion to the image. There will be **four** different models corresponding to four kinds of distortions. We analysed the common level of distortion to simulate to realest artificial distortion which will make the dataset meaningful.

Antidistorted Image

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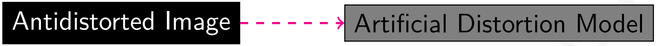

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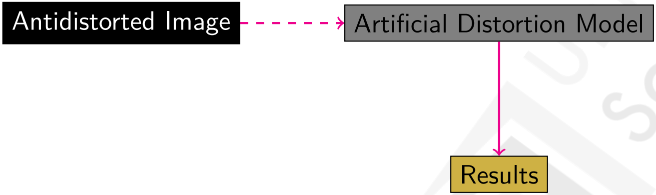
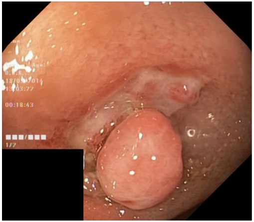
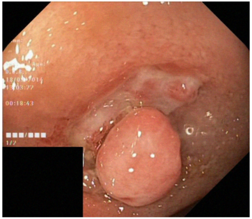


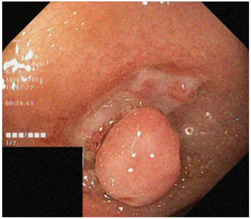
Result images after adding Noise





AWGN kernel width

$$\sigma_n = 0.01$$



AWGN kernel width

$$\sigma_n = 0.1$$

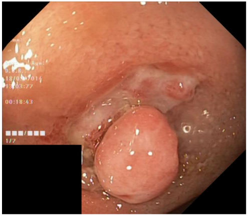
$$\hat{I} = I + n$$

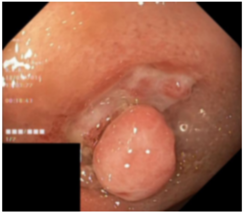
where n is the noise whose distribution

$$N(0, \sigma_n^2)$$

Figure 14: Noising image with Gaussian Noise $n \sim N(0, \sigma_n^2)$

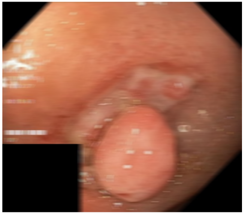
Result images after adding Blur





Defocus blur kernel width

$$\sigma_{db} = 2$$



Motion blur kernel width of PSF

$$l_{mb} = 20$$

Figure 15: Bluring image with Defocus Blur $b \sim N(0, \sigma_{db}^2)$ and motion blur PSF kernel width l_{mb}

Result images after adding Uneven Illumination

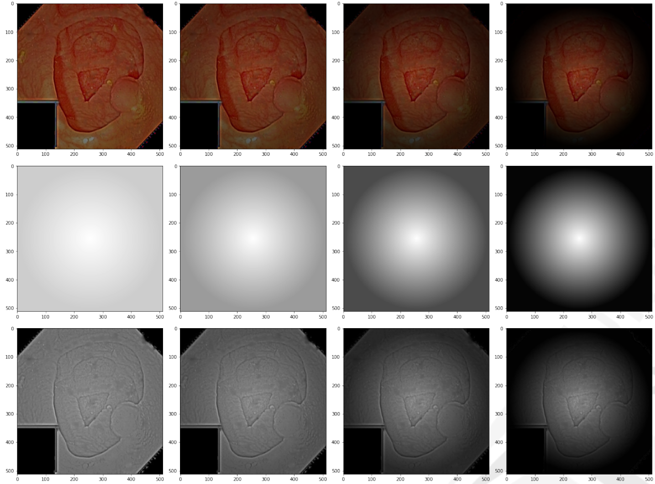
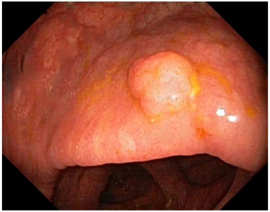
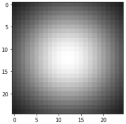


Figure 16: Artificial Uneven Illumination process. The first row is the result after adding the mask (second row) into the V-channel of image (third row).

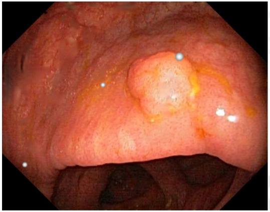
Result images after adding Specular Reflection



Input image



Artificial SR point spread function



Output Image

Figure 17: Artificial Specular Reflection by using the artificial PSF with the random position

References

[1] Jorge Bernal, F. J. Sánchez, and F. Vilariño. "Towards automatic polyp detection with a polyp appearance model". In: **Pattern Recognit.** 45 (2012), pp. 3166–3182.

[2] Jorge Bernal et al. "WM-DOVA maps for accurate polyp highlighting in colonoscopy: Validation vs. saliency maps from physicians". In: **Computerized medical imaging and graphics : the official journal of the Computerized Medical Imaging Society** 43 (2015), pp. 99–111.

[3] Sharib Ali et al. "Endoscopy artifact detection (EAD 2019) challenge dataset". In: **ArXiv** abs/1905.03209 (2019).

[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.

[5] Juan Silva et al. "Toward embedded detection of polyps in WCE images for early diagnosis of colorectal cancer". In: **International Journal of Computer Assisted Radiology and Surgery** 9 (2013), pp. 283–293.

[6] A. Koulaouzidis et al. "KID Project: an internet-based digital video atlas of capsule endoscopy for research purposes". In: **Endoscopy International Open** 5 (2017), E477–E483.

[7] Y. Guo and B. Matuszewski. "GIANA Polyp Segmentation with Fully Convolutional Dilation Neural Networks". In: **VISIGRAPP** (2019).

[8] Jorge Bernal et al. "Polyp Detection Benchmark in Colonoscopy Videos using GTCreator: A Novel Fully Configurable Tool for Easy and Fast Annotation of Image Databases". In: (2018).

[9] the gastrointestinal site. "Gastrolab". In: **http://www.gastrolab.net/index.htm. Accessed: 2019-12-12** (2019).

[10] Endoatlas. "Weo clinical endoscopy atlas". In: **http://www.endoatlas.org/index.php. Accessed: 2019-12-12** (2019).

[11] UCI. "Gastrointestinal lesions in regular colonoscopy dataset". In: (2019). URL: http://www.depeca.uah.es/colonoscopy_dataset/.

[12] Atlas. "The atlas of gastrointestinal endoscope". In: (2019). URL: http://www.endoatlas.com/atlas_1.html.

[13] Atlas. " El salvador atlas of gastrointestinal video endoscopy". In: (2019). URL: http://www.gastrointestinalatlas.com/index.html.

[14] Konstantin Pogorelov et al. "KVASIR: A Multi-Class Image Dataset for Computer Aided Gastrointestinal Disease Detection". In: **Proceedings of the 8th ACM on Multimedia Systems Conference** (2017).

[15] Debesh Jha et al. "Kvasir-SEG: A Segmented Polyp Dataset". In: **ArXiv** abs/1911.07069 (2020).

[16] Konstantin Pogorelov et al. "Nerthus: A Bowel Preparation Quality Video Dataset". In: **Proceedings of the 8th ACM on Multimedia Systems Conference** (2017).

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

[18] 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.

[19] Said Pertuz, Domenec Puig, and Miguel Ángel García. "Analysis of focus measure operators for shape-from-focus". In: **Pattern Recognit.** 46 (2013), pp. 1415–1432.

[20] Wenyao Xia, Elvis C. S. Chen, and Terry M. Peters. "Endoscopic image enhancement with noise suppression". In: **Healthcare Technology Letters** 5 (2018), pp. 154–157.

[21] Zili Yi et al. "Contextual Residual Aggregation for Ultra High-Resolution Image Inpainting". In: **Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition**. 2020, pp. 7508–7517.

Thank you for watching!

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